HUMAN CAPITAL IN TRANSITION

ON THE CHANGING SKILL REQUIREMENTS AND SKILL TRANSFERABILITY

Dissertation

zur Erlangung des akademischen Grades

doctor rerum politicarum

(Dr. rer. pol.)

vorgelegt dem

Rat der Wirtschaftswissenschaftlichen Fakultät

der Friedrich-Schiller-Universität Jena

im August 2010

von: Ljubica Nedelkoska, MA

geboren am: 26. Januar 1982 in: Prilep, R. Mazedonien

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Datum der Verteidigung: 15.12.2010, Jena

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Acknowledgements

This dissertation is a result of joining ideas, creativity, and effort by many. I am indebted to my supervisors, Andreas Freytag and Michael Fritsch, for their openness for new thoughts, lighthouse guidance and patience for mistakes. Uwe Cantner and Oliver Kirchkamp unselfishly provided me with frequent advice and helped me resolve many dilemmas. I was fortunate to coauthor my work with Frank Neffke, Florian Noseleit, and Simon Wiederhold who greatly enriched my understanding of economics and ensured the quality of our work. I am grateful to Christina Gathmann for accepting the invitation to act as my external dissertation referee.

This work would not have been possible without the responsive team of the Research Center at the Institute for Employment Research (IAB) in Nuremberg who provided me with data access and technical support at the IAB, and facilitated the long-distance program processing. In particular, I thank Nils Drews, Peter Jacobebbinghaus, Dana Müller and Daniela Hochfellner.

Simon Wiederhold generously shared his know-how from my early insecure steps into the field of economics and believed in my work. Frank Neffke elevated my trust in research and problem-solving, and inspired and challenged my thinking. Florian Noseleit helped me break the ice of empirical research and guided me through feedback. Viktor Slavchev, Stefan Bauernschuster, Marco Guerzoni, and René Söllner were thought-provoking colleagues and friends. Fang Wang ensured ideal work atmosphere in our office. My parents and sister supported me with love and care.

I thank the student assistants Alexander Suleymanov and Sebastian Dietrich for excellent assistance. This dissertation was financed by the German Research Foundation (DFG) through a 3-year scholarship, and by the network of excellence "Dynamics of Institutions and Markets in Europe" (DIME) through a 3-month scholarship.

Coauthorships and statement of contribution

Chapters 3 and 4 of this thesis are based on coauthored work. Chapter 3 is based on the paper "Technology, outsourcing and the demand for heterogeneous labor: Exploring the industry dimension" coauthored with Simon Wiederhold, and chapter 4 is based on the paper "Human capital mismatches along the career path" coauthored with Frank Neffke. In each coauthored work, both coauthors contributed equally to the completion of the papers. Chapter 2 is based on the single-authored paper "Occupations at risk: The task content and job security".

List of abbriviations and acronyms

BIBB	Federal Institute for Vocational Training
GL	Generalized Leontief
IAB	Institute for Employment Research
IABS	Employment Samples of the Institute for Employment Research
EU KLEMS	EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs
LIAB	Linked Employer-employee Panel
PIM	Perpetual inventory method
SBTC	Skill-biased technological change
Translog	Transcedental logarithmic

Chapter 1

Human capital: Introduction

The contemporary structural change of developed economies is different from those in the past in many respects but in one: it vigorously transforms the world as we know it, compelling people to face new, perhaps less certain reality. Structural changes inevitably bring about demand for knowledge and skills different from those required in the era before. During the industrial revolution skilled artisans protested against technologies that made crafts acquired through years of learning redundant. Nevertheless, the human capital investment of those nineteenth century artisans is just a fraction of the human capital investment in skilled labor today. This is one of the reasons why the structural change of today is far costlier than any of those of the past.

Germany is not spared from the far-reaching transition toward the service economy. Let us take for instance one of the pillars of German manufacturing: the automobile industry. Summing across both producers and suppliers, in 2007 the German automobile industry counted around 750,000 jobs. In 2008 and 2009 30,000 of these jobs were cut and another 70,000 are planned to be abolished by 2015 (Herbst 2009). German automobile producers are meanwhile expanding in Central and Eastern Europe, India, China, Mexico and South Africa to name a few. At the same time they are investing in robotic technology which over the last few decades fundamentally changed the notion of assembly line production in this industry. These tens of thousands eliminated jobs may render skills idle that, summing across all individuals, represent hundreds of thousands years of education and training to master. Understanding the link between the organizational and technological changes taking place in firms on the one hand and the demand for skills on the other is crucial for making the economic and social transition toward the service and knowledge economy less perturbing.

Not only the skills of the workforce of the past, but also the conceptual apparatus that served the economic analysis of labor well before, appears to be ill-equipped for today's challenges. For instance, many of the jobs in manufacturing are described as "blue-collar" or "low-skilled". Such denominations are inadequate for capturing the changing requirements on the labor force because they remain vague about the actual content of work. One could argue that as long as a distinction between high-skilled and low-skilled or blue-collar and white-collar gives a good prediction of labor demand and wages no further economic understanding of work content is necessary. To see how problematic this point view is, it is enough to think of the consequences of the new possibility to electronically transmit an intellectual service, like statistical analysis or a web design, over the Internet. Whereas it is often blue-collar jobs that are associated with a high risk of international outsourcing, not all white-collar jobs are safe from it. In fact, as we will argue in this thesis, the blue-collar white-collar distinction is not relevant for determining outsourceability of jobs. This is one of the reasons why throughout this thesis we pursue an analysis of the content of human capital.

We claim that the inquiry into the content of human capital shows that more education may not always improve the employment prospects, and that in order to explain job security we have to understand what is that employees do at their jobs. We furthermore argue that such inquiries improve our understanding of how structural change, set into motion by new technologies and the opening of world markets, alters the work content of jobs. We finally assert that knowledge about the content of human capital enriches our views on occupational change and career paths.

The rest of this chapter will first take a historic perspective on the research in human capital and will pay special attention to the literature dedicated to the relationships between technology and labor, and outsourcing and labor, as well as to the transferability of human capital. This allows us to position the content of this thesis within the wider current debate in labor economics. The second chapter analyses the skill composition of West(ern) Germany, its changes in the period 1975-2004 and tests predictions derived from theory proposed by Autor, Levy, and Murnane (2003). The third chapter is dedicated to the estimation of industry-specific relationships between technology and labor, as well as between outsourcing and labor. It provides estimates of technology-labor and outsourcing-labor elasticities for twelve industries in Germany in the period 2001-2005. The fourth chapter focuses on the measurement of human capital transferability and the effects of human capital mismatch on occupational mobility and wages. The fifth chapter presents a final discussion of the results, concludes the policy lessons and outlines proposals for further research.

1.1 Basic concepts

Economists crafted the term human capital in order to disentangle investments in human wellbeing and competence from those in material capital, while still emphasizing that human wealth exhibits comparable properties to material wealth in terms of accumulation and investment[1]. Although human capital is by no means a homogeneous quality, for certain types of economic analysis the general term suffices. Human capital refers to the stock of knowledge, skills, and abilities embodied in people, and which stock is activated in the production of goods and services. Some of the elements of human capital are genetically inherited and others are acquired through formal (education, job training) and informal (family) learning, as well as through an own effort. Due to the nature of the data that we use, this thesis will pay most attention to one aspect of human capital-skills. In psychology skills are re-

[1] One of the first thinkers in the human capital literature, Theodore Schultz (1960) equalizes human capital with education.

ferred to as applications of abilities to a specific domain (Ackerman, 1988; Fleishman 1982). Autor and Acemoglu (2010) define skills from an economist point of view as "worker's endowments of capabilities for performing various tasks", where tasks are "units of work activity that produce output".

1.2 Human capital and economic growth

The relevance of human capital for production was acknowledged very early in the economic literature, although not all early economists agreed that human competences should be treated as capital. Adam Smith (1776) recognizes the "acquired and useful abilities of all the inhabitants or members of the society" as the fourth type of fixed capital (Book II, chapter I) and Alfred Marshall (1890) makes a parallel between the investments in human capital and those in material capital: "...the motives which induce a man to accumulate personal capital in his son's education are similar to those which control his accumulation of material capital for his son." (p. 660-661). However, John Stuart Mill criticized the thought that people of a country should be looked upon as wealth because wealth existed only for the sake of people. Therefore, he makes a strict distinction between labor and capital.

In the first half of the twentieth century only sporadically did economists speak of human capital (for such instances see Pigou 1928). The economic thought of the second half of the twentieth century bravely started the investigation into perhaps the most crucial element of economic development - human capital. Gary Becker, Theodore Schultz, Jacob Mincer, Milton Friedman and Sherwin Rosen pioneered the field by openly recognizing skills and knowledge as capital, and training and education as investments in human capital. Theodore Schultz (1961) explains why economists shied away from openly acknowledging and discussing human capital. "...to treat human beings as wealth that can be augmented by investment runs counter to deeply held values. It seems to reduce man once again to a mere material component, to something akin to property." (p. 2). Schultz puts forward the importance of acknowledging human competences as capital. In the classical economic models labor only entered the production function as a quantity. In the early neo-classical models more educated labor was simply counted as a multiple of less educated labor. It is however, the qualitative aspect of labor that matters most for production. That labor quality and productivity can be enhanced through health care, education and training, and that these are investments in human capital were bold, but essential thoughts of the early human capital inquiry.

Luckily, neither entrepreneurs, nor the states waited for the economic literature to acknowledge the relevance of human capital and the investments into it for economic growth. When describing the type of focus that commissioners of the U.S. and the U.K. had when scrutinizing each others' competitive advantage at the beginning of the twentieth century, Claudia Goldin (2001) writes: "Earlier delegations focused on technology and physical capital. Those of the turn-of-the-century turned their attention to something different. People and training, not capital and technology, had become the new concerns." (p. 263).

In the twentieth century, scientific discoveries with commercial value such as "petroleum refining, wood distillation, sugar refining, rubber, canning, paper and pulp, photography, fertilizers, and later steel, ceramics and glass, paints and varnishes, soap, and vegetable oils" as well as "the internal combustion engine, electrification, and the use of small motors" (p. 273) necessitated qualified labor in order to be produced, implemented, and further developed. In addition, certain technological office discoveries such as comptometer, typewriter, dictating machine, addressograph, and mimeograph increased the productivity of, and the demand for, office clerks (p.274). Goldin further documents that agricultural firms realized that workers with formal secondary school education were better in learning about crops, animal health, fertilizers, machinery, accounting techniques, and that they were faster in technological adoption. Therefore, according to Goldin, innovations bred demand for qualifications across several different industries.

This is of course one side of the story. The other side of it is that empowering masses of people through education exerted an immense impact on the inventive and economic power of nations. Denison (1985) finds that the growth of schooling years in the period 1929-1982 explains 25% of the growth in the U.S. per capita income. Maddison (1996) compares the contribution of education to economic growth in a cross section of countries, and finds large differences: from 30% of the per capita income growth in France in the period 1973-1992 to 5.2% of the per capita income growth in Germany in the same period.

As late as the late twentieth century the endogenous growth theory formalized the positive link between human capital and technological advances. In 1986 Romer's endogenous growth model knowledge is a production input that leads to growth.

> "Most important, production of consumption goods as a function of the stock of knowledge and other inputs exhibits increasing returns... In contrast to models in which capital exhibits diminishing marginal productivity, knowledge will grow without bound. Even if all other inputs are held constant, it will not be optimal to stop at some steady state where knowledge is constant and no new research is undertaken." (p. 1003)

Besides increasing marginal productivity and positive knowledge spillovers, another channel through which knowledge contributes to growth is through enabling technological adoption. Nelson and Phelps (1966) hypothesize that "... educated people make good innovators, so that education speeds the process of technological diffusion, (p. 70).

Today, economics places problems of knowledge generation and diffusion among the most central economic questions. While in the first half of the twentieth century educational policy in most European countries treated education as a good reserved for small groups of privileged people (Goldin 2001) and limited the possibilities of individual human capital upgrading and changes of working status, today's Europe makes large efforts toward equal education opportunities and excellence in education. Today, when the role of human capital for growth hardly needs any further explanation, it is difficult to believe that there was time in not that distant history when economics reduced the human component of production to counting the quantity of homogeneous labor heads.

Once economists started speaking openly about human capital, an array of unanswered questions appeared on the research agenda. A remarkable attention was given to estimating the returns to education as a form of investment in general skills (e.g., Becker 1960; Schultz 1960, 1988, 1993; Psacharopoulos and Hinchliffe 1973; Psacharopoulos 1985, 1995 and Psacharopoulos and Patrinos 2004; Angrist and Krueger 1991 to name a few), the skill premia (e.g., Acemoglu 1998 and 2003; Lemieux 2006), the specificity of human capital (e.g., Becker 1962; Hashimoto 1981; Neal 1995; Parent 2000; Poletaev and Robinson 2008; Lazear 2009), and the capital-labor relationships (Griliches 1969; Berman, Bound, and Griliches1994; Krusell et al. 2003).[2]

1.3 Human capital and technology

The economic history evidences that over the last few centuries there has been a number of widespread cost-saving technological innovations and organizational strategies that resulted in radical shifts in the demand for labor even at the level of economies. Automated looms at the beginning of the nineteenth century replaced the effort of the skilled weavers in the textile industry with a punched card and few unskilled workers. In his analysis of the nineteenth century labor-saving technologies in the U.S. and the U.K., Habakkuk (1962) finds that labor scarcity forced the U.S. to advance labor-saving technologies. Since skilled labor was in short supply, particularly favourable technologies were those which could substitute for work content which could only be carried out by highly-trained workers. The implementation of the Fordist assembly line in the automobile industry early in the twentieth century caused an increase in the demand for tasks which can be thoroughly described in step-by-step instructions (explicit tasks). Turning to a more recent period, there exists growing evidence that

[2] The list of topics is by no means exhaustive.

the proliferation of personal computers caused shifts away from programmable (routine) tasks toward complex, problem-solving ones (e.g., Autor, Levy, and Murnane 2003). In line with these examples, Goldin and Katz (1996, 2009) stress that within the last two centuries there existed both, technologies and organizational practices that shifted the demand toward more skilled labor (e.g., continuous processes and batch technologies in manufacturing), and those that caused aspirations toward low-skilled labor (e.g., the transition from artisan shop to factory).[3]

Despite the evidence that technologies differently affected the demand for heterogeneous labor in the past, in the first half of the twentieth century there was a belief that better-educated workers are faster in technological adoption. For example, Nelson and Phelps (1966) write: "The better educated farmer is quicker to adopt profitable new processes and products since, for him, the expected payoff from innovation is likely to be greater and the risk likely to be smaller; for he is better able to discriminate between promising and unpromising ideas, and hence less likely to make mistakes." (p. 70). Also, Greenwood and Yorukoglu (1997) write: "Setting up, and operating new technologies often involves acquiring and processing information. Skill facilitates this adoption process." (p. 87).

For many technologies developed in the twentieth century it was probably true that they complemented skills. Some scholars anticipated very early that possible complementarity between technology and skills will lead to massive skill upgrading. Peter Drucker (1954) writes: "They [technological changes] will not make human labor superfluous. On the contrary, they will require tremendous numbers of highly skilled and highly trained men-managers to think through and plan, highly trained technicians and workers to design the new tools, to produce them, to maintain them, to direct them." (p. 22). Also Nelson and Phelps conclude that "...the rate of return to education is greater the more technologically progressive is the economy...it may be that society should build more human capital relative to tangible capital the more dynamic is the technology." (p. 75). The question of skill-capital and more specif-

[3]Moreover, Becker, Hornung, and Woessmann (2009) find that in the metal production sector in Prussia in thenineteenth century higher education speeded up the iindustrial revolution, while the opposite was the case in textile manufacturing.

ically, skill-technology complementarity gained in importance as the anticipation of massive educational upgrading came true throughout the twentieth century.[4] Few different works of Claudia Goldin and Lawrence Katz, many of which are summarized in their recent book "The Race between Education and Technology" (2009), provide evidence for technology-skill complementarity throughout the twentieth century. Investigating several samples for diverse periods and regions of the U.S., they suggest that industries which used more advanced technologies as early as the beginning of the twentieth century also employed more educated labor. These patterns were prevalent throughout the twentieth century and absent before this period.

Despite the abundance of anecdotal and descriptive evidence of capital-skill complementarity, it was not until the 1960s that economists developed a framework for testing the complementarity hypotheses. The dominant Cob-Douglas production function was inadequate because the substitution elasticity between the production factors is bounded to be 1. The challenge was to specify production function of a more flexible form, one with a possibility of varying input factor substitution elasticities. One group of more commonly used production functions that allow for variance in the elasticity of substitution are the constant elasticity of substitution production functions (McFadden 1963). Griliches (1969) proposed empirically testable equations that model the relationship between the relative demand for skills and capital investments. His findings suggest higher complementarity between capital and skilled labor than capital and unskilled labor. In the 1970s and the 1980s other forms of cost and demand functions enabled empirical testing of the capital-skill relations.

Diewert (1971) proposed the Generalized Leontief (GL) production and cost function, a more general case of a Leontief production function. Using the GL specification Morrison and Siegel (2001) find that technology had stronger impact on shifts in labor composition in favor of highly educated workers than trade or outsourcing in the U.S., in the period 1958-1989. Applying a comparable methodology, Addison et al. (2008) find absence of asymmetric effects of information technology investments

[4]Goldin and Katz (2009) evidence that in the U.S. the share of population with elementary education only decreased from over 75% in 1915 to 3% by 2005. At the same time, the share of college graduates increase from 2.6% in 1915 to almost 30% in 2005 (p. 32 f.)

on labor demand for Germany in the period 1993-2002.

Christensen Jorgenson and Lau (1971, 1973) proposed the Transcedental Logarithmic production function (translog). Using a translog function Becker and Muendler (2010) find that German multinational enterprises substitute domestic with foreign labor as a reaction to wage differences in labor cost; Betts (1997) offers evidence for bias away from blue-collar workers in the Canadian manufacturing in the period 1962-1986 that can be associated with technological change; Machin and Van Reenen (1998) provide evidence of skill-biased technological change (SBTC) as an international phenomenon and Dewan and Min (1997) find substitution effects between IT capital and labor (not differentiated by type) in the U.S. in the period 1988-1992.

The literature on SBTC expanded rapidly during the 1970s, the 1980s, and the 1990s. Many studies provided evidence in favor of SBTC (e.g., Bartel and Lichtenberg 1987; Goldin and Katz 1998; Bresnahan, Brynjolfsson and Hitt 2002). Other studies found absence of skill-technology complementarity or suspected the validity of SBTC evidence (e.g., DiNardo and Pischke 1997; Card and DiNardo 2002). However, the dominant conclusion of the literature from the 1990s on was that the technologies of the second part of the last century complemented high-skilled labor (Autor, Katz, and Krueger 1998; Berman, Bound, and Machin 1998; Machin and Van Reenen 1998).

1.4 Human capital and international outsourcing

Most of the studies on SBTC had one major general purpose technology in mind-computers. The major diffusion of computers in the leading economies started at the end of the 1960s-the beginning of the 1970s. The period of spread of computers coincided with a period of increased international trade, as well as with a period of relevant institutional changes. The economic literature does not only link the increase in the demand for skills with technological innovations, but also with the intensification of international trade and in particular with modifications in the way trade takes place today. In particular offshoring or international outsourcing stands out as a rather recent phenomenon which altered the manner of international exchange of goods and recently services. While domestic outsourcing refers to reallocation of jobs within the same country due to changes in the division of labor among firms and industries, offshoring is the migration of jobs, but not the people who perform them from countries with high to countries with low labor costs (Blinder 2006, p. 113). In the rest of this section we explain how and why outsourcing may have played a role in the alteration of the skill distribution of developed economies. This will then reveal why it is problematic to assess any effects of technological change on the labor demand without considering the outsourcing activities of firms.

The products in some major industries in developed countries such as automobile and computer hardware manufacturing exhibit modular character, meaning that a stable component interface is shared over time or within a product family so that the product components that fit this interface can be developed independently to a large degree. Each of the product components has a specific function, but the functionality of the complete product is ensured through the common interface (Sanchez and Mahoney 2000; Galvin and Morkel 2001). Galvin and Morkel (2001) argue that where international standards exist and the need for managerial coordination is limited, the possibilities for geographical dispersion of an industry are broad (p. 34). Galvin and Morkel (2001) describe the process of going global since the 1950s in the bicycle industry:

> "Rather than change components, the mass producers looked for even cheaper components. This led them initially to Japan and later to Taiwan. Firms such as Nitto, Sugino, and Ukai were approached to make basic components such as rims and seatposts by both U.S. and European assemblers. Shimano (as the dominant bicycle firm today) gained its initial foothold in the USA courtesy of Columbia, to whom they sold hubs." (p. 38).

Hence, a relatively recent phenomenon in international trade is that an international division of labor in the production of a single product is enabled through standardization of the product components to fit a single interface while leaving room for incremental component-innovations. Such division of labor allows that a firm outsources separate production units without relocating the complete firm.

The new division of labor is not limited to manufacturing products. Breakthroughs in information and communication technologies enable that electronically transmittable products and services which in the days before cheap and fast communication were non-tradable to become more and more tradable (Blinder 2006, p. 115).

The causal relationship between international outsourcing and shifts in the skill distribution can be explained with the help of a familiar mechanism: comparative advantage. It is a well-established knowledge that openness to international trade fosters specialization in the area of comparative advantage. The modern comparative advantages are the kinds of labor and skills a country possesses. Unlike comparative advantage based on natural resources, skills are more dynamic wealth whose acquisition can be stimulated through active educational and training policy. In the current state of affairs, countries like Germany, the U.S., and the U.K. exhibit comparative advantage in the production of goods (or parts of a good) which require skilled labor. Therefore, one expected consequence of increased international outsourcing is a bias toward skilled labor in countries with relative abundance of such labor.

Hsieh and Woo (2005) analyze the specialization patterns of Hong Kong (skill-intensive economy) and China (unskilled-intensive economy) before and after China's opening to trade with Hong Kong. They find that the outsourcing of manufacturing to China resulted in significant bias toward skilled labor and educational upgrading in Hong Kong. Fenstra and Hanson (2001) review several empirical studies on the impact of international trade on the wage inequality for different countries and conclude that international trade in form of outsourcing, similar to technological change contributes to the skill upgrading of nations and to widening of the skilled-unskilled wage gap. For Germany, Geishecker (2006a) finds that for the 1990s international outsourcing toward Central and Eastern Europe had a significant negative effect on the demand for production workers and that this effect is comparable to the one of technological change for which the author controls. An earlier study for Germany (Falk and Koebel 2000) on contrary finds that neither imported material inputs nor imported intermediate services have an effect on the demand for unskilled labor.

In conclusion, both SBTC and increased international trade could theoretically explain the patterns of increased skill demand in developed countries. In the words of Feenstra and Hanson (2001) "...trade in inputs has much the same impact on labor demand as does skill-biased technical change: both of these will shift demand away from low-skilled activities, while raising relative demand and wages of the higher skilled. Thus, distinguishing whether the change in wages is due to international trade, or technological change, is fundamentally an empirical rather than a theoretical question." (p. 1)

1.5 Change of perspectives: The task-based approach

The astonishingly large literature on SBTC fell short in explaining the content of technology-skill substitutability. The economic explanation of SBTC was limited to answering *how* a SBTC can happen and did not answer *why* it happened. The modelling of technological change at the macro level turned problematic because, at this level, alternative theories which did not consider technology as a factor could also replicate the empirical observations related to skill upgrading and increased returns to education. Moreover, while a theory of SBTC gives an intuition about why firms that implement new technologies would prefer skilled labor, it is silent on the question of *direct substitution of human effort with technologies*.

A respond to this critique is well elaborated in the work of Autor, Levy, and Murnane (2003). These authors argue that the current discourse on SBTC "...fails to answer the question of what it is that computers do-or what it is that people do with computers-that causes educated workers to be relatively more in demand." (p. 1280). They propose and test a model that builds upon a set of observations mainly stemming from organizational theory and computer science. They argue and find that: computers substitute for manual and cognitive tasks that can be accomplished by following explicit rules and complements labor in performing cognitive nonroutine and complex interactive tasks. The article brings at least three critical elements into the understanding of the technology-labor relations. First, it establishes micro-foundations of the task-technology relations. All previous models of SBTC present a rather macro understanding of the mechanisms at work. Second, it relocates the SBTC debate from focusing on the level of human capital to focusing on the type of human capital that is being substituted or complemented by technologies. Therefore, instead of looking at low-skilled, medium-skilled and high-skilled labor, it looks into the task content of jobs. Third, the theory is more general than it appears at first sight. Namely, although it is strictly focusing on explaining how computers affect the work content, computers here should be understood in a very broad sense, as all *code-based technologies* (e.g., Jaquard loom, computerized numerical control (CNC), automated teller machine (ATM), automatic cashier to name a few).

Autor, Levy, and Murnane (2003) propose that a categorization of tasks into routine cognitive (e.g., record keeping and calculation), routine manual (e.g., picking or sorting), nonroutine cognitive (e.g., managing, persuading), and nonroutine manual (e.g., janitorial services) can give us more insight into the impact of computers on the work content than an education-based grouping.

Their theoretical model builds on a Cobb-Douglas production function with two tasks: routine and nonroutine. By assumption computer capital is more substitutable for labor executing routine than nonroutine tasks. Another assumption is that routine and nonroutine tasks are imperfect substitutes. Third important assumption is that more intense use of routine tasks (independent on whether these are carried out by humans or technology) increases the marginal productivity of nonroutine inputs. The basic intuition behind this assumption is that there are workers who typically execute routine tasks and there are workers who use routine tasks as input in order to complete nonroutine tasks. An example would be a secretary who mainly stores, organizes and retrieves information for someone who necessitates this information in order to perform tasks such as giving presentations, making judgements or negotiating. The exogenous force in the model is the sharply declining price of computers in the last few decades which induces investments in computer capital. Since computers are perfect substitutes for routine labor, the wage of routine labor is fully dependent on the price of computers. As the price of computers falls, the routine labor's wage falls as well. In the model's labor supply setup workers can decide what share of their labor should be dedicated to routine and nonroutine tasks. However, due to sorting of workers based on their comparative advantage, they either provide routine or nonroutine labor. In equilibrium, marginal workers decide whether to specialize in routine or nonroutine tasks based on the relative price of nonroutine and routine labor. One important implication is that, due to the falling price of routine tasks, such workers will more often decide to specialize in nonroutine tasks. Further implication of the falling routine tasks' price is that the economy becomes routine-tasks-intensive. However, now the demand for routine tasks is satisfied by technology and not by labor because the marginal workers decide to specialize in nonroutine tasks. Since the more intense use of routine tasks increases the marginal productivity of nonroutine labor, the wages of workers who specialize in nonroutine tasks rise.

Therefore, the model successfully explains the following empirical observations: increase in the demand for nonroutine labor, increase in the price of nonroutine labor, decline in the price of routine labor and the decline in the demand for routine labor despite increased overall demand for routine tasks.

The research approach that regards the work content of jobs was quickly adopted in the analysis of the impact of international outsourcing on labor. As mentioned earlier, the possibility for modular production could enable firms to focus on what they do best and outsource what can be produced with comparable quality but with higher cost-effectiveness outside. To accomplish disjunction and reallocation of labor-intensive parts of the production process a firm must ensure that the necessary competences for process performance are present in the low-cost country of choice. Explicit tasks are not only easier to program, but are also easier to teach to foreign labor. Assembly line work or sewing cloths can be clearly written in a manual and taught within weeks. This is not the case with legal judgements, mediation, managing, or improving of processes. Higher international competition among labor that carries out routine tasks will lower the prices of such labor in developed countries and as a consequence diminish their presence in the same. Therefore, so far we see that theoretically, the effect of outsourcing on the demand for routine or codifiable labor can be compared to the one of computers from the perspective of a developed economy.

However, the task-based approach reveals a major difference in the labor substitution limits between technology and outsourcing. The capability of computers to substitute for human tasks is conditioned by "what programmers, engineers and scientists know how to describe using computer code...Many tasks involving vision, locomotion, problem solving, pattern recognition, language interpretation and communication cannot currently be described with computer code..." (Autor 2009, p. 12). This is not necessarily true for tasks that can be outsourced. Blinder (2006) argues that the critical criterion that divides outsoureable from non-outsourceable tasks (in particular service ones) is whether an activity is deliverable electronically with little or no diminution in quality (Blinder 2006, p. 118). This divide categorizes non-negligible share of jobs that involve problem-solving, pattern-recognition and even communication into outsourceable jobs. The range of service jobs that Alan Blinder categorizes as offshorable is wide: from typing and call-services on the low wage tail to professional business services on the high pay end. Such examples are security analysis, radiological analysis, accounting, computer programming and web design.

Another strand of literature focuses on the process of gradual progress of outsourcing, from outsourcing of simple tasks toward outsourcing of tasks with higher cognitive complexity. This literature argues that outsourcing may start with unbundling simpler production processes such as assembly line, but will unlikely stop there. When describing the outsourcing practices of Danish firms, Maskell et al. (2007) write: "Initially, a corporation's outsourcing is driven by a desire for cost minimization. Over a period of time the outsourcing experience lessens the cognitive limitations of decision-makers as to the advantages that can be achieved through outsourcing in low-cost countries. . . The quality improvements that offshore outsourcing may bring about evoke a realization in the corporation that even innovative processes can be outsourced." (p. 239).

The current discourse on SBTC and outsourcing is by far not finished. The nuanced version of SBTC initiated by the work of Autor, Levy, and Murnane suggested an adjustment of the empirical approach and the modelling of the relations between labor and technology. For Germany, a growing number of studies adopted the task-based approach. To our knowledge such studies are: Spitz-Oener (2006); Antonczyk, Fitzenberger, and Sommerfeld, (2010); Antonczyk, DeLeire, and Fitzenberger, (2010); Baumgarten (2009); Baumgarten, Geishecker, and Gorg (2010); Becker, Ekholm and Muendler (2009); and Dustmann, Ludsteck and Schönberg (2009).

1.6 Transferability of human capital

The degree of specificity of human capital is one of the central questions in labor economics. This is not surprising because the answer to this question is relevant from several policy and management perspectives. First, the more general human capital is, the less costly are job displacements due to firm closures and shrinking (Topel 1991, p. 147). This is because human capital generality means that the skills learnt at the pre-displacement job are also useful in a larger number of alternative jobs. This additionally suggests that countries with more portable skills across jobs should have smoother labor market adjustments in times of technological change and internationalization of the division of labor. Second, the more general human capital is, the more difficult it is for firms to tie employees to certain job positions. For instance, for more general jobs firm investments in training are less effective means of binding employees to their firms (Becker 1962, Hashimoto 1981).

The advanced research debate on this issue involves a discussion on the sources of human capital specificity. For instance, Neal (1995) and Parent (2000) investigate the relative importance of firm-specific and industry-specific human capital and argue in favor of industry-specificity. Pavan (2009) argues that firm-specificity has been understated in Neal and Parent's work. Kambourov and Manovskii (2009) provide ample evidence that human capital is strongly occupation-specific. Gathmann and Schönberg (2010) show that human capital is more general than previously thought and use the concept of task-specificity based on the idea that different occupations use similar tasks[5]. Poletaev and Robinson (2008) provide similar evidence to Gathmann and Schönberg, and as analogue to the concept of task-specificity put forward the notion of skill-specificity.

Similar to other developed countries Germany undergoes a noteworthy transformation of the occupational structure. One consequence of such changes should be increased occupational mobility. Figure 1.1 shows a positive trend of involuntary (employment-unemployment-employment) occupational switching for 35 to 45 year old employees differentiated by educational achievement.[6]

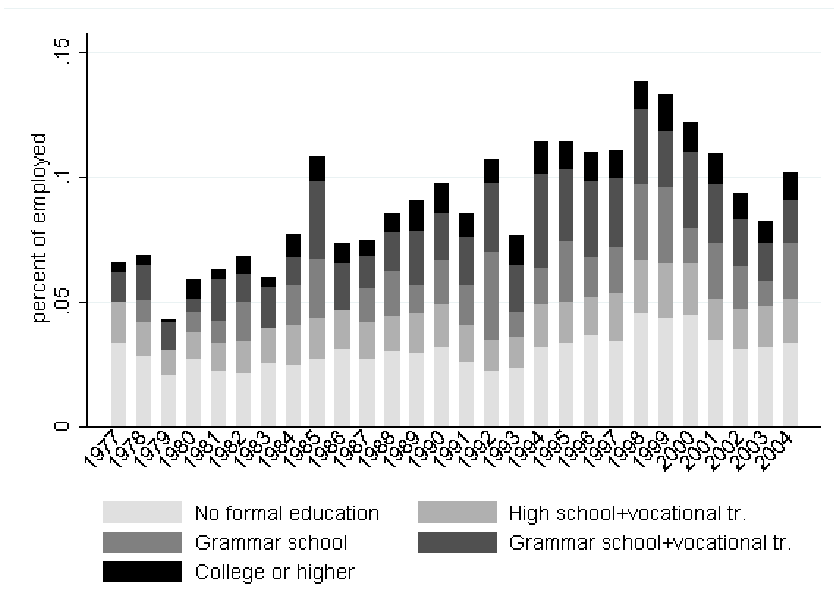


Figure 1.1: Occupational switching for 35 to 45 year olds by educational level
Source: IABS Regional (1975-2004)

[5]To our knowledge the first article that theoretically elaborates the concept of task-specific human capital is Gibbons and Waldman (2004)

[6]Such trend is also present, although somewhat less pronounced for the group of 25 to 35 year old employees, while no trend is evident for very young employees (up to 25 years).

When people change occupations part of their competences may become useless at the new occupation. Involuntary occupational changes are costly and these costs depend positively on the distance between the past and the new occupation in terms of skill overlap. This finding is profoundly elaborated in the work of Gathmann and Schönberg (2010), but is also the main theme in the work of Poletaev and Robinson (2008), Kambourov and Manovskii (2009), and Geel and Backes-Gelner (2009). However, the very recent literature that empirically investigates human capital specificity by looking at the skill overlap of jobs and occupations still leaves much space for further research contributions.

1.7 Outline of the thesis

The reminder of the thesis consists of four chapters. Chapters 2 to 4 are based on working papers. Chapter 2 is single-authored, while the rest two chapters are joint effort. The final chapter (chapter 5) summarizes the main findings and contributions of the previous three chapters, derives policy lessons and puts forward a new research agenda.

Chapter 2

The second chapter of this thesis is motivated by a recent observation that the relationship between the wage level and the employment prospects of occupations in developed countries changed in the last couple of decades. The wide-spread belief of the 1980s was that higher-quality jobs correlate with greater employment prospects in developed countries. The belief was frequently justified by the claims that technological innovations complement skills and that international trade favors specialization in skill-intensive goods and services in developed countries. Recent evidence shows that, contrary to the common expectations, the main labor downsizing in the last two decades in developed countries took place in the middle and not at the bottom of the wage distribution. Moreover, many low-paid occupations in fact grew in employment.

The chapter puts forward the recently discussed idea that the level to which work content is codifiable, meaning that it can be explicitly and exhaustively described and communicated to another person or a machine is crucial predictor of job stability. The main hypothesis which we test is that codifiable work content correlates with lower job security. This is because codifiable tasks are both, relatively easy to program, and hence substitute by technology, as well as because they are relatively easy to teach to other (foreign) labor.

In order to test this hypothesis we use individual-level data which provides rich information on the task content of jobs and the layoff risk. We additionally use individual-level longitudinal data which is perhaps the most reliable source of employment and wage statistics in Germany in a period of thirty years.

We confirm that occupations characterized by high intensity of interactive (face-to-face) and problem-solving tasks have been increasing their employment shares at the expense of occupations with high level of codifiable tasks. In line with previous findings we observe that occupations that report intense use of codifiable task content are often found in the middle of the wage distribution. This is why the monotonic relationship between wages and employment growth does not hold anymore. We further provide evidence at the individual level that jobs which involve high instance of codifiable tasks are associated with lower job security. The pattern is present at different educational levels and in various broadly defined industries. It is also present in both, the pre-reunification period and the periods after the German reunification. The results are in line with a theory of technological change where computer-based technologies substitute for codifiable tasks and complement for abstract (problem-solving) tasks.

Chapter 3

It is unclear whether the driving force behind the diminishing presence of employees who perform codifiable tasks is technology or international outsourcing. Studies that either focus on technology or on outsourcing are often criticized for overstating the effects of one factor or the other. For example, Becker, Ekholm and Muendler (2009) have to conclude that "It remains an open question beyond our identification strategy whether the time-varying effects are mostly related to technical change, to management practices, to offshoring, or a combination of these and other factors." Baumgarten (2009) also solely focuses on international outsourcing, while Spitz-Oener (2006) only considers computerization as a possible cause of changes in the skill structure. Furthermore, in the literature on SBTC became common practice to identify investments in new technology with investments in computers and to disregard possible sectoral idiosyncrasies in the technology-labor relations.

Chapter 3 attempts to incorporate both shortcomings in the previous literature: first by allowing for variation in the capital-labor relationships across industries, and second by incorporating measures of outsourcing and technological investments at the establishment level.

We estimate IT capital-labor and outsourcing-labor elasticities for 12 sectors in Germany. For this purpose we merge occupation-level data which captures the occupation-specific task structure with data from a linked employer-employee panel for the period 2000-2004. While we find no bias in the IT capital, we find that the outsourcing-labor relations differ across industries. In industries for which we find effects, labor with large codifiable content is adversely affected. However, in few industries also labor with high problem-solving content is at risk. The demand for labor that makes intense use of interactive tasks is mostly unaffected or reacts positively to outsourcing shocks. These findings are in line with the predictions of Blinder (2006, 2009). The magnitude of the effects is however not large especially when we consider that outsourcing is a rather rare event in our sample of establishments.

Chapter 4

Times of vivid technological change and forceful development of the international division of labor require frequent upgrading and modification of competencies. Due to skill obsolescence, a loss of job may at the same time mean a loss of chance to return to the former occupation. Occupational changes incur requalification costs for the individual and large forgone earnings if one is forced to switch from a more to a less complex job. In chapter 4 we therefore analyze the impact of skill mismatch for occupational switchers on the way people move from one occupation to another and on their post-occupational-switch earnings.

Building on studies like Gathmann and Schönberg (2010), chapter 4 introduces a new aspect of occupational switching: asymmetries in the human capital mismatch between occupational pairs. Current measures of occupational distance overlook the fact that job move from occupation i to j is qualitatively different from a job move from j to i. Despite the possible similarities in the skill content of two occupations, asymmetries arise from the differences in the complexity of those skills. Based on rich information about the tasks that employees perform in their jobs we introduce measures of human capital shortage and human capital redundancy for occupational switchers.

We ask few different research questions. How does human capital mismatch affect the mobility of labor across occupations? How does human capital mismatch affect the wage offer of occupational switchers, as well as the wage growth at the new job? How do the earnings of employees who accumulated experience in related occupations compared to the current one differ from the earnings of those who accumulated experience in unrelated occupations?

People switch occupations such that they avoid human capital (skill) redundancies, but also avoid moves to occupations for which they have to acquire additional human capital. We further find that employees who move to occupations where they incur skill shortage are offered lower initial wage as a result of such shortage, but experience steeper wage growth at the new position presumably due to learning effects. Individuals who switch to occupations where part of their skills are rendered redundant do not obtain higher wage offer as a result of the skill surplus.

Chapter 4 further introduces the concept of skill experience which is comparable to the concept of task experience introduced by Gathmann and Schönberg (2010). The novel element here is that we distinguish between useful and useless skill experience. We show that useful skill experience explains more of the variance in wages than general, occupational or plant experience. Therefore, we confirm the finding by Gathmann and Schönberg (2010) that people maximize the long-run earnings not necessarily by building tenure in the same occupation, but by staying within a set of skill-related occupations.

Chapter 5

In this final chapter we first discuss the main findings of the thesis, and bring to attention its major contributions and limitations. We then derive a number of policy lessons. The chapter concludes with a summary of research questions which remained outside the scope of this thesis.

Chapter 2

Occupations at risk: The task content and job security

2.1 Introduction

It is common knowledge that developed economies have vastly restructured from manufacturing to service dominated sectors - a process that is still in progress. We also know the meaning of this transition in terms of production of goods and services. Economies are furthermore familiar with its consequences on employment restructuring. What has not been elaborated extensively enough are the implications of such structural change on the occupational and skill structure of economies. The purpose of this study is to contribute to an understanding of the changes in the West German occupational and skill structure in the last few decades.

It has been argued that work tasks that can be expressed in step-by-step procedures or rules (routine tasks) are more vulnerable to the influence of technology and international outsourcing. It has been further argued that routine tasks are mostly concentrated in jobs that are found in the middle of the wage distribution. At the same time, the middle-paid jobs have been those to decline most in several developed countries in the last decades (Goos and Manning 2007; Dustmann, Ludsteck and Schönberg 2009; Goos, Manning, and Salomonss 2009). Goos and Manning (2007) refer to the improvement of the labor market position of the occupations at the bottom and top of the wage distribution relative to the middle as labor or job polarization. They connect the job polarization with the more nuanced theory of skill-biased technological change proposed by Autor, Levy, and Murnane (2003) which they refer to as routinization hypothesis. They propose that the substitution of labor that performs repetitive and explicit tasks with technology can explain the decrease in the employment share of jobs found in the middle of the wage (skill) distribution relative to the jobs found at the top and the bottom of the wage (skill) distribution.

We contribute to the literature by elaborating the relationships between wages and occupational employment growth, wages and task distributions, and tasks and job security in West(ern) Germany for the periods before and after the German reunification. We ask the following questions: (a) What do occupations that increased their employment share in the observed years have in common in terms of task and skill profile? (b) What do occupations that decreased their employment share in the observed period of time have in common in terms of task and skill profile? (c) Is the relationship between work-task content and employment growth of occupations (job security of employees) in accordance with the proposed nuanced theory of skill-biased technological change (Autor, Levy, Murnane 2003)?

We find that the monotone positive relationship between wages and employment share growth of occupations deteriorated in the years between 1975-2004 and that a U-shaped relationship between wages and employment growth gives a better fit. However, this pattern of job polarization is not as pronounced as in the case of the U.S. and the U.K. The reason is that many high-growth service-intense occupations were already well paid in the 1970s. We further find that the instance of frequent use of explicit or codifiable task content correlates highly with the perceived layoff risk at the individual level. The correlation is present at various educational levels and within different broadly defined industries. This is also evident both before and after the German reunification. These results are in line with the nuanced theory of skill-biased technological change proposed by Autor, Levy, and Murnane (2003).

The rest of this paper is structured as follows. Section 2.2 discusses the theory and the consequences of knowledge codification and derives the hypotheses. Section 2.3 introduces the data, section 2.4 describes the job polarization in Germany, section 2.5 addresses the between and within changes in the intensities of different tasks. Section 2.6 makes the connection between task content of jobs and job security. Section 2.7 concludes.

2.2 The codification of knowledge and its implications for job security

An important dimension of knowledge is its tacitness, as Michael Polanyi elaborated in his 1967 work. One part of our knowledge can be articulated, verbally explained or written down to an extent that another person to whom it is communicated can comprehend its essence and be able to follow clear instructions. Another part remains less accessible to others either due to our inability to explain what we know or due to the fact that what we do, e.g., the way we reach solutions for a set of problems, is not well known to us either. By making what we know understandable for, and *reproducible* by, others, we turn tacit knowledge into explicit or codifiable knowledge.

Cowan and Foray (1997) define knowledge codification as “the process of conversion of knowledge into messages which can be then processed as information” (p. 596). The authors point out the dynamic character of knowledge that becomes more codifiable as it ages. Knowledge creation typically starts as being entirely tacit, as an idea. The process turning idea development into useful knowledge can also be highly tacit. As knowledge becomes better understood, and as it becomes feasible to disentangle it into explicit rules and steps, the process of codification starts. In some cases, “a procedure becomes routinized and repeatable, which implies that it can be broken down into component pieces, each of which is sufficiently simple that it can be described verbally or embodied in a machine." (p.595).

The articulation of tacit knowledge is relevant for several reasons. The most important of these is probably that it enables knowledge transmission through learning from others. In most instances this is beneficial because it allows for a large upgrading of human capital through education and training. Two other consequences of knowledge codification, however, have more ambiguous consequences. First, once codified, knowledge becomes easily transferable from one person to another, increasing the substitution elasticity among labor. Hence, the monopoly power over own skills is reduced and so is the price of labor.[1] This reasoning is in line with the recent evidence that domestic labor in developed countries has been substituted through cheaper labor in developing countries in such a way that less-skilled labor has been more affected than labor with more complex skills. In his theory of offshorability of jobs in the U.S. economy Blinder (2006) argues that the degree to which a job will be outsourceable in future depends on the degree to which it involves direct interaction with customers. Another important dimension of jobs, Blinder agrees, is the level to which their work content can be broken down into simple, routinizable tasks (p. 43). With everything else remaining constant, jobs that involve routinizable tasks are more outsourceable than jobs involving complex thinking, judgment and nonroutine human interaction. Therefore, despite the low skill requirements for jobs such as waiting staff or hairdressers, these jobs are at low risk of outsourcing.

Second, codifiable knowledge can be easily written in a machine code, rendering skills of human labor potentially substitutable by technologies. It has been widely claimed that information technologies (IT), being powerful systems of knowledge codification, have drastically shifted the skill composition of developed countries toward higher use of nonroutine work tasks. Autor, Levy, and Murnane (2003), when explaining which types of tasks can be substituted by computers, write:

[1] The same type of reasoning can be applied to product inventions. This has been well known among industries whose products are made apparent by looking at a bare recipe. For example, Cohen, Nelson and Walsh (2000) show that, among several available ways of protecting innovation from imitation which include patents, licensing, lead time etc., secrecy is still considered the most effective way of product innovation appropriability by almost all 34 interviewed industries.

> "...[computers] rapidly and accurately perform repetitive tasks that are deterministically specified by stored instructions (programs) that designate unambiguously what actions the machine will perform at each contingency to achieve the desired result...A task is "routine" if it can be accomplished by machines following explicit programmed rules...Because these tasks require methodical repetition of an unwavering procedure, they can be exhaustively specified with programmed instructions and performed by machines" (p. 1282/1283).

We prefer to refer to technologically substitutable tasks as codifiable or explicit and not as routine because the latter term, although precisely defined in the work of Autor, Levy, and Murnane, causes some confusion about what is in fact programmable and what is prone to technological substitution. A task does not have to be routine in order to be codifiable. Reaching analytical solution of a complex mathematical model, or presenting relationships between data in the form of a statistical model are not necessarily routine tasks, but they are explicit. Moreover, a task does not have to be repetitive in order to create economic incentives for technological substitution. It is true that programmable tasks that are highly repetitive (e.g., bricklaying, product labeling, or sorting) create incentives for technological diffusion because such repetitive processes are labor intensive. However, complex but explicit tasks also create such incentives because they are labor intensive due to the task complexity itself. Moreover, labor capable of performing tasks will necessarily be scarcer and therefore better priced than labor that performs simple repetitive tasks. It has been widely discussed that technologies are often developed with the purpose of substituting scarce, and therefore expensive labor (Habakkuk 1962, Acemoglu 2003).

This further brings us to the point that not all tasks that are codifiable are actually being substituted by technology. The first and obvious reason for this is that there are moving limits to automation science: for instance, the patent for the first mechanical tabulation machine was launched in 1889 (e.g., Kistermann 1991), most of the ATM and ATM-like patents were issued in the 1960s (Batiz-Lazo and Reid 2008), and most of the construction automation is still in its infancy even today (Balaguer and Abderrahim 2008). The second and perhaps more important reason is that there is a discrepancy between the point of invention and the diffusion period of a labor-substitutable technology. In some cases the initial price of the technology does not justify its implementation, in other safety issues are difficult to resolve. At the dawn of the iindustrial revolution in Great Britain labor-saving innovations such as the Spinning Jenny had to be hidden from the masses of agonized wavers whose labor price they sunk. Today there are robots that can replace the janitor's work or the work that involves care for others which have not diffused yet (and may not diffuse in the near future either); the semi- or completely robotized train is an 1960s invention, but its first and slow implementation started just few years ago in Germany, with 10 fully functional robotized subways currently operating in Nuremberg (Siemens AG 2008).

Up to this point, we have elaborated on the kind of labor codifiable by technologies and stated that such labor, if it does not involve intense interaction with customers (interactive tasks), may be more internationally outsourceable than labor that does involve such interaction. Therefore, here we can now state the hypotheses we would like to test with respect to the job security of employees whose work incorporates tasks with codifiable content. Without disentangling the sources of labor substitution, we expect that:

H1: Employees who report a high instance of codifiable tasks report higher risk of layoff

H2: The layoff risk of employees with a high instance of codifiable tasks decreases to the extent that their work also incorporates interactive tasks

It is further argued that labor prone to technological substitution and international outsourcing can be found at any educational level. Blinder, for example, proposes that the probability to be offshored is independent of the educational level required for the job. Autor, Levy, and Murnane (2003) find that shifts away from codifiable tasks are prevalent at all education levels.

H3: The relationships between the frequency of codifiable tasks and the layoff risk hold at different levels of education.

2.3 Data

We use two datasets for this analysis. One is the Qualification and Career Survey (QCS)and the second is the IAB Employment Samples (IABS). The first dataset is our source of information about individual, work-related tasks and skills as well as the individual level layoff risk. We mainly rely on the second dataset for employment and wages information. The information from the first dataset is merged with the IABS at the occupational level.

2.3.1 Qualification and Career Survey

The QCS is a repeated cross section conducted at 6- to 7-years intervals, which started for the first time in 1979[2]. Its purpose, among others, is to track skill and task requirements of occupations. The survey is a rich source of information about the types of tasks employees perform in their jobs. Unfortunately, it repeatedly changed its structure, and many relevant questions are not consistently asked in each wave. We use all five waves of this survey, 1979, 1985, 1991/1992, 1998/1999, and 2005/2006, in order to compare the within and between-occupational changes in the use of tasks that are identically defined across waves. Here we use questions that are strictly comparable in at least four waves (see Table A1 in appendix A). Since for certain analyses it is useful to reduce the dimensionality of the data, we use the 1979 wave to conduct factor analysis (as explained in appendix A). After careful inspection of the questions in each wave we concentrate on those that are relevant for our purpose and identical or closely comparable between waves.

2.3.2 The measurement of task codification and task intensities

Two measures are of central interest in this paper: repetitiveness and explicitness of work tasks. Two questions in the QCS that, we believe properly capture the

[2]The QCS is administrated by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment Research (IAB).

degree of task codification appear in all five waves in a consistent manner. The first question reads: How often does it happen that the same work step *repeats itself in each and every detail* of your daily work? This is our indicator of the repetitiveness of tasks. The second question reads: How often does it happen that you are being *instructed about the work process in each and every detail* of your daily work? This is our indicator of the explicitness of tasks. The answer is given on a Likert scale: practically always, often, from time to time, seldom, practically never[3]. The use of these questions as measures of task codification has a number of advantages when compared to the choice of questions that Spitz-Oener (2006) and similar studies use to indicate routine tasks.[4] First, the classification is less arbitrary. For instance, one may rightfully agree that researching and analyzing are mainly analytical tasks, while advising customers, entertaining or presenting are mainly interactive tasks. However, categorizing calculating, bookkeeping and correcting of text and data as routine tasks is more ambiguous, as all these activities, although admittedly more routine, involve intellectual judgment. Second, close inspection of the variables in the QCS that have been used to measure routine work before reveals large inconsistencies in their formulation. Any analysis of the within changes in the task content will be sensitive to the change in the question design. Third, when more arbitrary choice of variables is used, many notably routine tasks, such as sorting, pressing, labeling, stocking, and related assembly-line activities remain out of the focus of the analysis due to the fact that they have been asked only in one of the survey waves. Table 2.1 presents the tasks with which at least one of our measures of task codification is positively and significantly correlated.

We see that at the occupational level, the explicitness and repetitiveness of tasks relate to many of the tasks that one would think of as being routine. We also check how our measures of task codification correlate with those proposed by Spitz-Oener (2006). Employees and occupations which report high intensity of explicit

[3]In the 2005/2006 survey, the option "practically always" is absent.

[4]Spitz-Oener (2006) indicates the following tasks as routine cognitive: calculating, correcting text/data, bookkeeping, measuring length/weigth/temperature. She classifies operating or controlling and equipping machines into routine manual tasks.

and/or repetitive tasks tend to report significantly fewer tasks such as calculating, bookkeeping, correcting text and data. Therefore, our measures of codifiable tasks capture the *manual* rather than the cognitive routine work. The trends in the use of mathematics, statistics and arithmetic are captured by a separate variable and presented below. Other tasks that we can follow consistently over a longer period of time are: process improvement, educating, and the use of law. A more detailed description of these variables can be found in Table A1 in appendix A.

Table 2.1: Correlations between task codification and other tasks

	Explicitness	Repetitiveness
Work under norm	.78*	.62*
Machine knowledge	.29*	.02
Melt, cast, sprey	.23*	.13
Shape, form	.24*	.16
Building of canals, street paving	.27*	.11
Sawing, quilting	.47*	.26*
Packing, shipping preperation	.37*	.48*
Product stocking	.30*	.27*
Sorting, labeling	.11	.34*
Transporting	.51*	.36*
Observations	116	

Source: QCS, 1979 wave

Besides the measures of codification, we also try to capture what Autor, Levy, and Murnane (2003) call nonroutine tasks. When adequate we use original variables from the QCS. However, in some instances it is useful to have more generic measures of nonroutine tasks. To create such measures we use factor analysis as explained in appendix A. Basically, through analysis of the common variance of a group of task measures we reduce their dimensionality to few variables that capture most of the information contained in the original variables. The factor analysis of 14 variables in the 1979 wave results in three factors. The first factor loads high (above .5) on the following variables: research, evaluate, investigate; negotiate, represent; coordinate, organize, delegate; process improvement; arithmetic, math and statistics, and management. We call this abstract dimension. The second factor scores high on: negotiate, consult (customers/suppliers); negotiate, represent; and marketing, sales. We refer to this as the sales dimension. The third factor scores high on: taking care of others and medical examination, cosmetology. We call this the care dimension. Occupations that score highest on the first factor are engineers, entrepreneurs and managers; occupations that score highest on the second factor are salespersons, commercial agents, tourism specialists and restaurant and hotel proprietors; and occupations who score highest on the third factor are nurses, medical and nonmedical practitioners, and social workers.

2.3.3 IAB Employment Samples

The second source of data we use is the IAB Employment Samples Regional file 1975-2004 (IABS Regional), which is a 2% random sample of the German population subject to social security. As this sample is explained in details in Drews (2008), we only mention its most important features here. The sample does not contain information on employees who are not subject to social security. This affects civil servants and the self-employed. However, for the rest of the employees it is the largest and probably the most reliable source of employment information in Germany. Furthermore, the social security wage data is the most accurate information on wages in Germany because non-reporting or false reporting is punishable by law. Wages are right-censored and this affects up to 14% of our observations in some years. We implement a wage imputation technique introduced by (Gartner 2005) in order to generate the missing information.[5] We consider Western Germany specifically because for this part of Germany we have a longer time dimension and because earlier waves of the QCS also only included information on former West Germany. The IABS Regional and the QCS are matched at the occupational level. Although the survey data has a very detailed (in some waves 4-digit level) occupational classification, the

[5]The wage prediction is conducted separately for each year. The method used is a tobit regression. For the prediction we include the following variables: age, age squared, education, gender, occupational dummies and 16 industry dummies. These can explain between 19% and 50% of the total individual-level wage variation is separate years.

IABS Regional offers an occupational classification between the 2- and the 3-digit level. We drop houseworkers, interns and volunteers. We also drop occupations that in the QCS list fewer than 10 observations or are not observed in all five waves[6]. This leaves us with 115 occupations we consider in the analyses that involve merging of the datasets. One convenient feature of both the IABS Regional and the QCS is that they keep a consistent occupational classification system comparable both between the samples and over time.

2.4 Wages and employment

2.4.1 Job polarization

Autor, Katz and Kearney (2006, Figure 3) show that the relationship between the skill level as measured by the educational achievement[7] and the change in the employment share of occupations shifted from monotonically increasing in skills/earnings in the 1980s to a U-shaped relationship in the 1990s. Goos, Manning, and Salomonss (2009) find that the job polarization in 16 European countries is a phenomenon of the 1990s. Contrasting these results, Dustmann, Ludsteck and Schönberg (2009, p. 871) suggest that the pattern of polarization was present in Germany also in the 1980s. Our observations confirm those of Dustmann, Ludsteck and Schönberg (2009).

Table 2.2 presents the results of OLS estimations where on the LHS we have the 5-year log employment share changes and on the RHS the median occupational daily wage. We estimate the same models for 5-year periods starting in 1975, 1977, 1979, 1981, 1983, 1995, 1997 and 1999. We avoid the years that are close to the German Reunification in order to mitigate any shocks to the employment structure that it may have caused. The first specification (Linear fit) shows the results of fitting a model

[6] Spitz-Oener argues that the occupations that disappear from the QCS or appear for a first time can be considered as a random draw (p. 266 f.)

[7] ,Both occupation-specific educational attainment and the occupational standing on the wage distribution are used as an indicator of the job quality or the skill level (see Autor, Katz and Kearney (2008, p. 191) and compare with Goos and Manning (2007, Figure 1) and with Dustmann, Ludsteck and Schönberg (2009, Figure VII). We will use the occupational standing in the wage distribution because of the limited quality of our education variable.

that assumes a linear relationship between wages and employment share changes, while the second specification (Quadratic fit) allows for a non-linear relationship. We first compare the coefficients of the median occupational wage for the linear specification and find that they almost monotonically decrease over the observed period. In the 1990s the relationship is statistically insignificant. Moreover, when we compare the linear specification to the quadratic one, we see that the latter notably improves the fit (as measured by the R^2) in six out of eight periods. The U-shaped relationship is not present in the earliest period, 1975-1980, but it is present in both the 1980s and the 1990s, and later on.

Despite the presence of a U-shaped relationship between wages and employment growth in Germany, the difference to what has been observed for other developed countries (mainly the U.S. and the U.K.) is that the fast-growing social care-related occupations which in the U.S. and the U.K. accounted for some of the lowest-paid jobs in the 1980s, were already in the middle of the wage distribution in Germany in the late 1970s. Moreover, the declining textile occupations in the thirty years observed were already at the bottom of the wage distribution in the second half of the 1970s. Because both, the declining manufacturing jobs and the growing social care-related jobs, are found in the middle of the wage/skill distribution, its "hollowing out" in Germany is not as pronounced as in other countries.

Table 2.2: Occupational employment share growth and the median occupational wage

	1975-80	1977-82	1979-84	1981-86	1983-88	1995-00	1997-02	1999-04
				Linear fit				
Median occ. wage	.185***	.157***	.137***	.106**	.107**	.041	.095	.041
	(.04)	(.05)	(.05)	(.05)	(.04)	(.04)	(.06)	(.04)
Constant	-14.86***	-14.07***	-13.60***	-11.25**	-1.45**	-7.629	-12.20**	-7.891*
	(4.24)	(4.93)	(4.98)	(4.99)	(4.37)	(4.81)	(5.66)	(4.26)
R^2	.059	.054	.050	.039	.044	.007	.015	.008
				Qudratic fit				
Median occ. wage	.140	-.459*	-.622***	-.408	-.218	-.380*	-.347	-.458**
	(.28)	(.26)	(.24)	(.25)	(.25)	(.20)	(.28)	(.18)
Median occ. wage^2	.000	.003**	.004***	.002**	.002	.002**	.002*	.002***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Constant	-12.89	13.97	22.74*	14.89	5.03	15.75	1.38	17.75
	(13.13)	(12.76)	(11.79)	(13.11)	(12.85)	(11.30)	(15.09)	(9.07)
R^2	.060	.080	.102	.070	.058	.037	.027	.050
Observations	115	115	115	115	115	115	115	115

Dependent variable: 5-year employment share growth; source: IABS Regional (1975-2004); OLS results; robust standard errors in parenthesis; significant at: *** 1%, ** 5%, * 10% level;

2.4.2 Fastest growing and declining occupations

In this section we examine the fastest growing and declining occupations in the pre- and post-reunification periods in West Germany. We would like to ascertain if they have anything in common and how they compare with findings in other studies. Table 2.3 presents the ten fastest growing occupations, while Table 2.4 demonstrates the ten fastest declining occupations in the periods 1975-1988 and 1995-2004. From Table 2.3 we see that besides some highly paid occupations such as management consultants, engineers, physicians and data processing specialists, some low-paid service occupations such as restaurant and bar keepers, catering personnel, medical receptionists, and nonmedical practitioners show the highest employment increases. At the same time, in line with what was mentioned before, fast-growing occupations in the middle of the wage distribution were home wardens and social work teachers, social and care workers, work and vocational advisers. This is in particularly true of the pre-reunification period.

Among the fastest declining occupations we find those related to the clothing production, (spinners, fiber preparers and braiders, leather makers, and leather processing operatives, cutters, and textile finishers), metal production, (iron/metal producers, melters, drawers, drillers, cutters), and construction (bricklayers, concrete workers, pavers, stucco workers, etc.). Some clerical personnel such as stenographers were also downsized significantly.

The most comparable study to ours is Goos and Manning (2007) for the U.K. The occupational growth patterns in the U.K. are similar to those in Germany (Tables 4 and 6 in Goos and Manning, 2007). In particular, this is true when it comes to the ten fastest declining occupations. The U.K., however, experienced steeper expansion and downsizing rates than Western Germany in the observed period of time.

2.4.3 Job quality and wage growth

Goos and Manning (2007) discuss that, contrary to the expectations of higher wage growth at the bottom of the wage distribution - allegedly due to increased demand

Table 2.3: Fastest growing occupations

1975-1988			1995-2004		
Occupation	Median occ. wage 1975 (DM)	Employment growth (percentage)	Occupation	Median occ. wage 1995 (DM)	Employment growth (percentage)
Home wardens, social work teachers	91.47	1.14	Other engineers	177.27	.68
Social-, care workers, work-, vocational advisers	88.66	1.13	Assistants (no further specification)	93.89	.60
Management consultants, accountants, tax advisers	104.14	1.09	Data processing specialists	165.25	.54
Non-medical practitioners, masseurs, physiotherapists	85.85	.89	Social-, care workers, work-, vocational advisers	154.25	.45
Medical receptionists	61.92	.84	Home wardens, social work teachers	112.67	.38
Physicians till pharmacists	152.05	.83	Factory guards, detectives till judicial enforcers	101.40	.33
Data processing specialists	116.81	.81	Management consultants, accountants, tax advisers	115.23	.32
Electrical engineers	137.31	.73	Post masters till telephonists exc. postal deliverers	88.63	.29
Restaurant/inn/bar keepers, hotel proprietors, catering	68.96	.70	Economic and social scientists, statisticians	135.95	.29
Economic and social scientists, statisticians	105.55	.69	Non-medical practitioners, masseurs, physiotherapistss	87.13	.26
Median wage in 1975	87.25		Median wage in 1995	107.41	

Source: IABS Regional (1975-2004)

Table 2.4: Fastest declining occupations

1975-1988			1995-2004		
Occupation	Median occ. wage 1975 (DM)	Employment growth (percentage)	Occupation	Median occ. wage 1995 (DM)	Employment growth (percentage)
Spinners, fiber preparers till braiders	67.55	-.56	Concrete workers	115.67	-.79
Iron/metal producers, melters till metal drawers	9.07	-.47	Miners till Mineral preparers, mineral burners	114.17	-.73
Railway controllers, conductors	88.66	-.47	Bricklayers	113.42	-.59
Leather makers till leather processing operatives	6.51	-.44	Spinners, fiber preparers till Textile processing operatives (braiders)	88.63	-.57
Cutters till textile finishers exp. clothing sewers	56.29	-.37	Cutters till Textile finishers exp. Clothing sewers	71.36	-.52
Wood preparers till basket products makers	74.59	-.27	Leather makers, catgut string makers till Skin processing operatives	80.37	-.46
Drillers till other metal-cutting occupations	92.88	-.25	Paviors till other civil engineering workers	111.17	-.40
Concrete workers	87.25	-.25	Wood preparers till basket and wicker products makers	96.90	-.39
Miners till Mineral preparers, mineral burners	95.70	-.24	Stucco workers, plasterers, rough casters till Screed, terrazzo layers	114.92	-.37
Bricklayers	8.21	-.24	Stenographers, shorthand-typists, typists	102.90	-.37
Median wage in 1975	87.25		Median wage in 1995	107.41	

Source: IABS Regional (1975-2004)

for "lousy" jobs - the wages of the low paid occupations fell in the U.K. Autor, Katz and Kearney (2008), on the contrary, evidence that in the U.S. the increase in wages at the bottom of the wage distribution did indeed take place (p. 190). Figure 2.1 shows the relationship between the job quality measured by its rank in the 1975 and 1995 wage distribution, respectively, and between the occupational wage growth in the pre-reunification (1975-1988) and the post-reunification (1995-2004) periods. Apparently, as in the U.K. and unlike in the U.S., the real wages of low paid occupations fell in the more recent period.

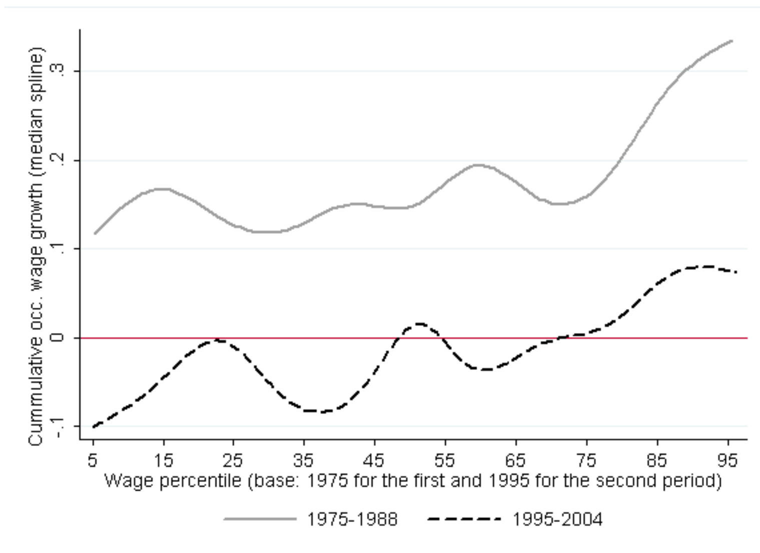


Figure 2.1: Cumulative changes in the real daily earnings by wage percentile
Source: IABS Regional (1975-2004)

As Goos and Manning (2007) argue, it is difficult to explain these facts with a theory of technological change that indirectly creates demand shifts for more interactive type of labor (Autor, Katz and Kearney, 2006, p. 193). Moreover, it is difficult to reconcile these observations with any theory that only considers the demand-side factors. A simultaneous increase in employment and wage decline can be encountered under conditions of outward shift of the supply curve. There are reasons to believe that there were supply push factors in the development of services. If automation and computerization truly released labor from the manufacturing sectors, a surplus of labor might have contributed to the expansion of the cheap-services sectors.

Figure 2.2 plots the ratio between the total inflow of labor from different sectors into services and the total outflow of labor from services into other sectors. An inflow-outflow ratio of 1 means that the inflow into services equals the outflow from services, while an inflow-outflow ratio of below 1 would mean that the outflow from services exceeds the inflow into services. The mean inflow-outflow ratio for the period until 1990 is 1, meaning that services exchanged around the same quantity of labor force with other sectors on an annual basis. In the period after 1990, the inflow of labor into services increased beyond the outflow in relation to all other sectors. The mean annual inflow-outflow ratio in this period is 1.13, meaning that on average services gained around 13% net labor inflow from other sectors annually. From Figure 2.2 we see that these inflows did not only stem from manufacturing, but also from construction and agriculture, and mining. Although a complete explanation of the decreasing wages for growing occupations will require a good measure of the demand side in services, here we suggest that a labor supply push from other sectors is one likely explanation.

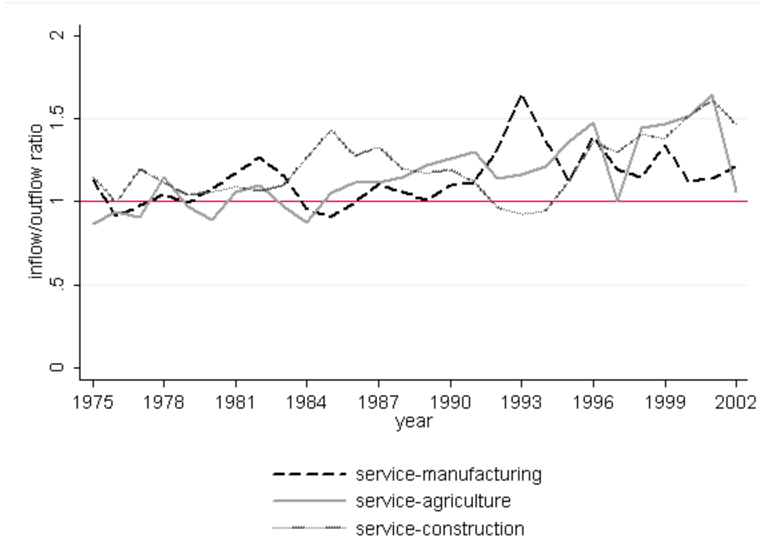


Figure 2.2: Labor inflow-outflow ratio between services and other sectors
Source: IABS Regional (1975-2004). Note: the time series is interrupted in 2002 due to change of the industrial classification

In summary, similar to Dustmann, Ludsteck and Schönberg (2009) we find that the hollowing out of the middle of the skill/wage distribution was present both in the 1980s and the 1990s in Germany. However, since some declining manufacturing occupations were already low paid in the 1970s and some service occupations were already medium-paid in the 1970s, in Germany the job polarization picture is not as clear-cut as in other developed countries. Additionally, the simultaneous presence of declining wages and increased demand for many service jobs urges for an explanation.

2.5 Tasks: Composition and changes

So far we addressed the relation between wages (chiefly as an indicator of job quality) and employment growth of occupations in order to establish the fact that the employment prospects mainly declined for the middlepaid occupations. In this section we analyze the task content of occupations in order to understand the commonalities that declining and growing occupations share in terms of task content.

2.5.1 Within and between changes in task intensities

The aggregate changes in task quantity come from three sources: total employment growth of the economy, task intensity shifts within occupations, and changes in the occupational mix of the economy. We are mainly interested in the task changes that stem from the within- and the between-occupational task shifts. To illustrate what these types of changes mean, let us take the occupation of 'turner' in the metal production as an example. The primary task hare is the production and finishing of machine components through movements such as turning, drilling, grinding, and molding.[8] The employment share of this occupation in the total employment decreased from .7% to .4% (between-occupational employment change), and the employment decreased by 24% in the period 1979-2005.[9] However, a higher percentage of employees in this occupation report use of explicit work in 2005 than in 1979 (within-occupational task change). Hence, the aggregate codifiable task quantity of this occupation in the economy increased due to the within-occupational upgrading of such tasks and decreased as a result of its diminishing share within the total employment.

Spitz-Oener (2006) evidences a pronounced shift in the frequency of use of different tasks over the period 1979-1999. She finds that the use of analytical tasks on average grew by .5 percentage points, the use of interactive tasks increased by 1.3 percentage points, while the routine cognitive and the routine manual tasks experienced an average annual decline of .7 percentage points in the observed period (p. 244). Due to the shortcomings of the previously used measures of routinization as outlined in subsection 2.3.2, we revise these findings by using alternative specifications of tasks.

In the rest of this section we describe the development of task intensity between and within occupations. The descriptive analysis is followed by a shift-share analysis

[8]The occupation of 'turner' has existed in Germany since 1939. Before the introduction of computerized numerical control (CNC) in the 1970s and the 1980s, its work operations were semi-automated. The introduction of CNC radically changed its occupational content from manual work toward computer programming. In 2002 due to changes in the task content, the occupational training and the occupation itself were also officially restructured. This occupation now carries the name of 'precision machinist' and is also commonly known as CNC turner.

[9]The estimates are based on the QCS, waves 1979 and 2005/2006.

that disentangles the change in tasks due to within-occupational shifts from the change due to shifts in the occupational structure of the economy. Table 2.5 lists the overall changes in the mean occupational tasks reporting for seven tasks that we found to be strictly comparable over at least four survey waves. In contrast to what Spitz-Oener finds, using the generic measures of task codification we find a general trend of increased rather than decreased upgrading of within-occupational manual codifiable tasks (average annual increase in repetitive tasks of .62% and annual average increase in explicit tasks of .55%). The use of arithmetic, math and statistics as a measure of cognitive codifiable tasks shows a pronounced decline in the observed period (an annual decline of 1.18% over a period of 27 years, while some interactive tasks (educating) and cognitive tasks (interpreting laws and regulations and improving processes/trying out new things) gained in overall presence within occupations.

Table 2.5: Annual percent changes in the use of tasks

Task	Overall annual changes
Repetitiveness of tasks	.62
Explicitness of tasks	.55
Arithmetic/math/statistics	-1.18
Educate/teach	.51
Use of law	.70
Process imrpovement	1.55

Source: QCS, all waves. Notes: The changes in educate, teach cover the period 1985-1999. "arithmetic, math and statistics" is absent in 1985.

As mentioned at the beginning of this section, besides the within-occupational shifts, an important source of changes in the aggregate task measures may come from the transformations in the occupational structure of an economy. In order to glance the trends in the occupational structure changes we categorize all occupations according to three groups: codifiable task dominated, abstract task dominated and interactive task dominated[10]. This categorization is based on the information from the 1979

[10]Codifiable tasks dominated occupation is an occupation ranked higher at at least one of the

wave. Figure 2.3 shows the development of the employment shares of these three groups in the years 1975-2004.

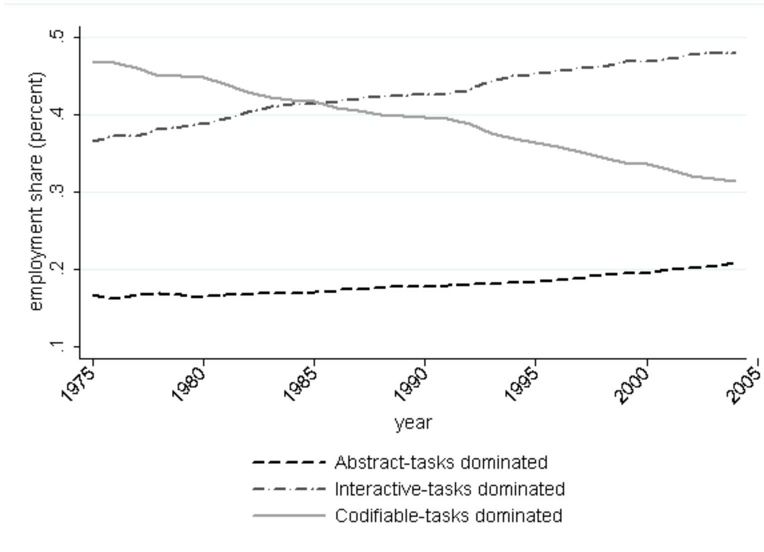


Figure 2.3: Development of the employment shares
Source: IABS Regional (1975-2004)

Evidently, there has been a drastic change in the occupational structure of occupations over time. While the interactive and abstract task dominated occupations increased their share in the economy from 36.5% to 47.8% and 16.6% to 20.9%, respectively, the codifiable task dominated occupations decreased their share from 46.8% to 31.3%.

Now we turn to the shift-share analysis. This exercise serves to compare the magnitude and direction of the changes in the total task quantity due to within-occupational

codification measures than on the abstract dimension and the interactive dimension. At the same time it is ranked not lower than the mean rank at one of the codification measures. Accordingly, abstract (interactive) tasks dominated occupation is an occupation that ranks at least at the mean of the abstract (interactive) dimension, and ranks higher on the abstract (interactive) dimension than on the interactive (abstract) one, and higher than or equal to the one of the codifiable measures. In a case of same ranking on both, the interactive and the abstract dimension, an occupation is classified as abstract tasks dominated.

upgrading with the task quantity shifts due to the changes in the occupational portfolio of the economy. We follow Spitz-Oener (2006, p. 249) in this respect. Therefore, we decompose the aggregate change in the use of task j into a term which reflects the changes between occupations and a term which reflects the changes within occupations: $\Delta T_{jt} = \sum_o(\Delta E_{ot}\bar{t}_{oj}) + \sum_o(\Delta t_{ojt}\overline{E}_o)$. Here T is the total task quantity of type j; E is employment of occupation o; and t is the task quantity of occupation o; $o = 1, ...115$, t =1985, 1991, 1998 and 2005, j =explicit-, repetitive tasks, arithmetic/math/statistics, educating, use of law and process improvement. Figure 2.4compares the within- and between-occupational task changes in the period 1979-2005/2006.

Figure 2.4 shows that the within-occupational task changes account for the largest share in the overall changes. It further shows that the between changes do not necessarily take the same direction as the within changes. In the case of repetitive and explicit tasks, the share of employees who report instances of such tasks increased, while the share of occupations with high intensity of repetitive or codifiable tasks decreased in the employment structure. The opposite is the case with occupations which report use of arithmetic, math and statistics.

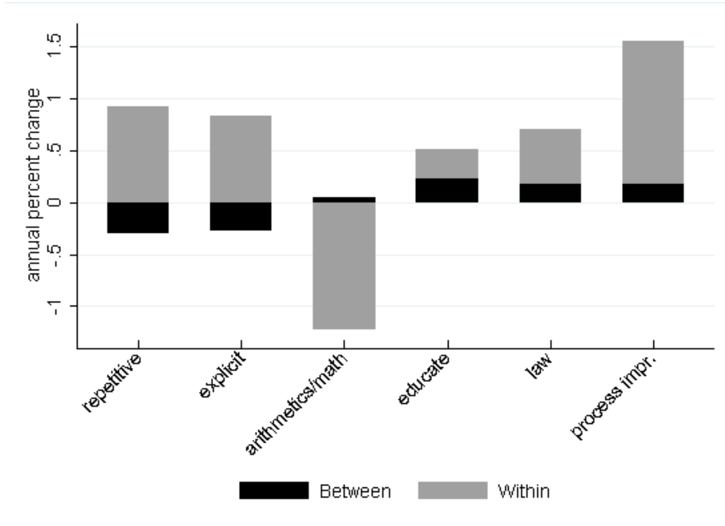


Figure 2.4: Within- and between occupational task changes
Source: QCS, all waves. Note: Results from a shift-share analysis. See also notes at Table 2.5

The observation that employees report more of what we refer to as codifiable task content today than thirty years ago seems to contradict what has earlier been reported for Germany (see, e.g., Spitz-Oener 2006). There are (at least) two possible explanations for the pattern we observe. First, if technology substitutes for certain tasks, the variety of tasks in the task portfolio of a job will decrease, which may lead employees to perceive higher monotonicity in their work activities. Second, over time, through active operations management, the work content within occupations probably becomes more structured and explicit. To decide which explanation is more plausible it would be useful to know whether it is occupations with low initial explicit content that show steeper growth of such content, or whether it is occupations with low initial explicit content that report an upgrading of codifiable tasks. A test of absolute convergence suggests that it is the occupations with high initial levels of codifiable content that show higher increases in such content ($\beta = .18, t = 6.38, N = 456$).[11]This suggests that the first proposed explanation

[11] The calculation of β or absolute convergence is the following: $lnT_{t+1} - lnT_t = \alpha + \beta T_t + \varepsilon$, where T is the share of employees within an occupation that report use of certain tasks, in our case

cannot be ruled out. It further suggests that there may be a high concentration of codification advances in certain occupations.

2.5.2 Making the link: Knowledge codifiability and job polarization

Goos and Manning (2007) argue that the hollowing out of the wage distribution can be explained by the nuanced theory of SBTC proposed by Autor, Levy, and Murnane (2003). While these autors make the link between knowledge codification, computerization, and the decline of jobs with such a content, Goos and Manning observe that jobs with routine task content are mainly located in the middle of the wage distribution. using wage information from the 1979 IABS Employment Samples wave and task information from the 1979 QCS wave we plot the task intensity by occupation (N=115) along the wage distribution. The task intensity measures are standardized to have mean zero and standard deviation of one. From Figure 2.5 we see that occupations which score high on the abstract tasks dimension are found at the higher wage deciles. Occupations which score above average on the sales dimension are found among the worse and the best paid occupations. As explained in subsection 2.3.2., the factor analysis additionally provides a care-for-others dimension that does not take a very distinct shape along the wage distribution, but may help us understand why some occupations close to the middle of the wage distribution also grew in the observed period. For completeness we include it in Figure A1 in appendix A. Probably the most interesting observation is that the occupations close to the middle of the wage distribution score above average on the explicit tasks measure and below average at the lowest and the highest wage deciles. This is not the case with the measure of task repetitiveness. Here worse paid occupations score higher than middle paid occupations.

explicit tasks (see Sala-i-Martin 1990, for a definition of βconvergence).

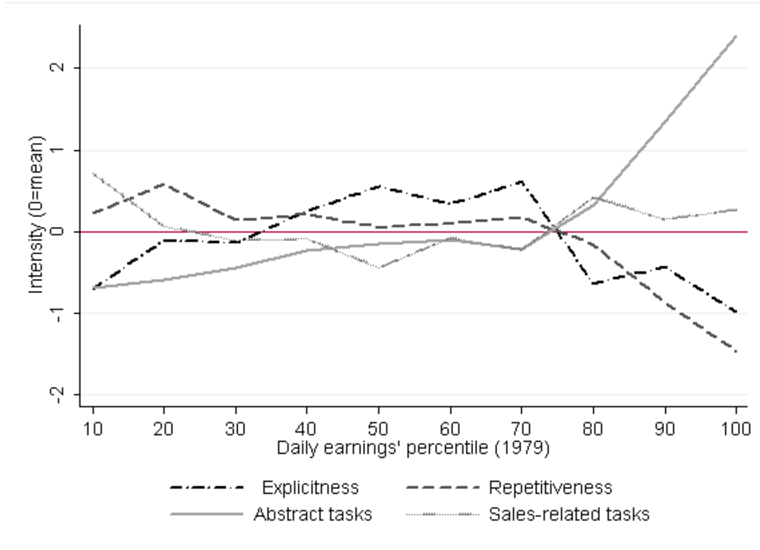


Figure 2.5: Tasks' intensities along the wage distribution
Source: IABS Regional and QCS, 1979

We conclude that the occupations with high explicit task content are concentrated in the middle of the wage distribution, while occupations with nonroutine cognitive (abstract) task content are concentrated at the top. Occupations making high use of interactive tasks such as caring for others can be found at different points of the wage distribution, while occupations that report frequent use of sales-related tasks occupy the bottom and top of the wage distribution. Lastly, occupations that report high frequency of repetitive tasks are clustered around the left wage distribution tail. These observations suggest that the decline of employment mainly in the middle of the wage distribution co-occurs with the location of jobs with high explicit tasks' content and not necessarily those with high task repetitiveness. Nevertheless, this may be a coincidence.

2.6 Knowledge codifiability and job security

In section 2.5 we showed that the share of occupations with frequent use of codifiable tasks decreased in the observed period. It would be useful to check whether the relationship between task content and job security holds at the individual level. At this level we can control for relevant individual-specific factors such as education, age, and gender. All these have been previously found to play a role in changes in the occupational structure (see, e.g., Goos and Manning 2007). At this level we can also identify the industry where a person is employed.

Our dependent variable, perceived layoff risk, is an ordinal one. The most common way to model the relationship between an ordinal dependent variable and a number of independent variables is an ordered logit model.[12] One favorable property of the ordinal logit is that by exponentiating the coefficients, one can obtain the odds ratios. Table 2.6 presents the results of an ordered probit model, where the perceived layoff risk is regressed on the types of tasks employees perform in their jobs and a number of control variables. Since the coefficients do not have an intuitive interpretation, the odds ratios are reported. An odds ratio over 1 indicates a higher risk for higher values of a dependent variable.[13]

One of the most stable findings is that the explicitness of tasks correlates strongly with a perception of higher layoff risk. This is true for all three waves (1979, 1998/1999 and 2005/2006) and remains stable under different specifications. For example, employees who reported frequent use of explicit tasks in 1998 were 1.6 times more likely to also report a very high layoff risk (in contrast to reporting no risk, low risk, or high risk) ceteris paribus. We also see that the repetitiveness of tasks changes sign and is difficult to interpret. Other stable findings are that complex tasks such as educating, organizing and coordinating, improving processes/trying out new things, and managing are associated with a lower perceived layoff risk. Also,

[12] Formally, this model can be written as follows: $P(Y_i > j) = g(X\beta) = \dfrac{exp(\alpha_j + X_i\beta)}{1 + \{exp(\alpha_j + X_i\beta)\}}$, $j = 1, 2, ..., M-1$ where M is the number of categories in the ordinal dependent variable and β are the coefficients to be estimated.

[13] To rule out business cycle effects we also pool the observations of all three periods and add year dummies. Performing explicit tasks, marketing-related tasks and R&D tasks correlates positively with the layoff risk. Educating and training, organizing and coordinating, process improvement, management, customer support, math and statistics, and law use and interpretation correlate negatively with the layoff risk. All the coefficients are significant at the 1% level except for law use and interpretation which is significant at the 10% level. The results are available from the author on request.

the use of arithmetic, math, and statistics is associated with lower layoff risk. This last finding is interesting and in line with what we observe in section 2.5: although within the same occupations we see a decrease in the use of math, arithmetic, and statistics; occupations that make use of math increased their employment share. One unexpected result is that the instance of research, development, and design activities is associated with higher layoff risk in the later two periods for which we do not have an explanation to this end. Moreover, jobs which involve marketing tasks appear as jobs with low security. This can be explained by the fact that in the advertising sector "the job security depends directly on the agent's ability to maintain and expand clientele" (Bureau of Labor Statistics 2009, p. 509).

The ordinal logit assumes that the relationship between each pair of outcome categories is the same (proportional odds or parallel regressions assumption). Therefore, although $M-1$ models are estimated, the βs do not vary across the equations. We tested whether the assumption of proportional odds is too strong in our models, and we also estimated unconstrained partial proportional odds models (see Peterson and Harrell, 1990; Lall et al., 2002).[14] Since using a less constrained model than the ordinal logit increases the complexity of representation without adding much additional information, we stay with the initial specifications. To further check the robustness of the findings, we used different definitions of our core variables. We tried two alternatives to the original scaling of explicitness and repetitiveness of tasks.[15] The results remain consistent with those presented in Table 2.6.

In section 2.2 we additionally hypothesized that there might be an interaction between the use of codifiable and interactive tasks when predicting the layoff risk.

[14] In all three specifications (1979, 1998/1999, and 2005/2006), we could not reject the proportional odds assumption at the 5% level. At the 10% level we could reject this assumption for the 2005/2006 specification. The results of the model tests and the alternative specifications are available from the author on request.

[15] The first alternative is defining these variables as dummies, where 0 indicates absence, seldom use or periodical use of the task and 1 indicates frequent or constant use of the task. This is the specification that we report in the tables. In the second alternative, 0 indicates absence or seldom use of the task, while 1 indicates periodical, frequent or constant use of the task.

Table 2.6: Explaining the perceived layoff risk

	1979				1998/1999				2005/2006			
	Model Ia		Model IIa		Model Ib		Model IIb		Model Ic		Model IIc	
Codifiable tasks												
Explicitness of tasks	1.660***	(.06)	1.611***	(.06)	1.583***	(.05)	1.574***	(.06)	1.342***	(.05)	1.349***	(.05)
Repetitiveness of tasks	1.175***	(.05)	1.175***	(.05)	.924**	(.04)	.934*	(.04)	.994	(.04)	.992	(.04)
Mainly abstract tasks												
Organize/coordinate	.696***	(.04)	.713***	(.04)	.782***	(.03)	.793***	(.03)	.938	(.04)	.943	(.04)
Process improvement	.905***	(.03)	.948	(.04)	.833***	(.03)	.839***	(.03)	.895**	(.04)	.888***	(.04)
Arithmetic/math/stats	.839***	(.03)	.894***	(.03)	.909***	(.03)	.918**	(.03)	.980	(.04)	1.000	(.04)
Management	.745***	(.04)	.800***	(.05)	.895**	(.05)	.920	(.05)	.960	(.04)	.977	(.05)
Research	.884	(.12)	.868	(.12)	1.236***	(.09)	1.227***	(.09)	1.091**	(.04)	1.079*	(.05)
Use of law	1.034	(.15)	1.147	(.17)	.830***	(.04)	.873***	(.04)	.940	(.05)	.931	(.05)
Mainly interactive tasks												
Educate/teach	.769**	(.09)	.769**	(.10)	.750***	(.10)	.756***	(.04)	.924***	(.02)	.912***	(.02)
Medical/cosmetic care	.676***	(.08)	.896	(.14)	.918	(.05)	.921	(.07)	1.107*	(.06)	.963	(.08)
Marketing	1.047	(.06)	1.025	(.06)	1.105*	(.07)	1.129*	(.07)	1.073*	(.04)	1.079*	(.04)
Sales/cusomer support	1.019	(.06)	.948	(.06)	.898***	(.03)	.886***	(.03)	.943	(.04)	.953	(.04)
Controls												
Age	.983***	(.00)	.982***	(.00)	.980***	(.00)	.980***	(.00)	.991***	(.00)	.990***	(.00)
Gender	.974	(.04)	1.013	(.05)	.895***	(.03)	.929*	(.04)	.944	(.04)	.933	(.04)
Education dummies	yes		yes		yes		yes		yes		yes	
Industry dummies	yes		yes		yes		yes		yes		yes	
Occupation dummies	no		yes		no		yes		no		yes	
Log pseudo likelihood	-12,790.1		-12,627.6		-16,660.7		-16,450.6		-12,784.1		-12,664.9	
Observations	22,636		22,636		16,595		16,517		12,980		12,932	

Dependent variable: perceived layoff risk; Source: QCS 1979, 1998/1999 and 2005/2006; Ordered logit model; Robust standard errors in parentheses; Odds ratios are reported. Significant at ***1%, **5% , *10% level.

Some occupations may report a high level of explicit knowledge, but also a high level of interaction with customers, clients or patients. For example, the daily tasks of a butcher or baker may follow a routine procedure, but may also involve a high customer-contact frequency. We expected that when explicit tasks coincide with interactive ones, this would somewhat mitigate the layoff risk. This expectation is not borne out in the data. All the interactions between explicit and interactive tasks are insignificant and this holds for all three waves.

We are further interested to know whether the measure of explicit tasks predicts higher layoff risk for different educational levels. If the earlier view of skill-biased technological change is true, only employees at lower educational levels would fear unemployment. The more nuanced view of SBTC proposes that codifiable knowledge is at risk of technological substitution within groups with identical education. Our results show that the frequent presence of explicit tasks predicts higher layoff risk at different educational levels. Table 2.7 presents the interactions between the explicitness of tasks and the education dummies separately for each wave. As a reference category in all years we take employees without formal education who do not report explicit tasks. In all three waves and at almost all educational levels, we find that employees who frequent perform explicit tasks are more likely to be found in the highest layoff risk category in comparison to the employees in the reference group. Most of the time this is not the case with employees who have some formal education but do not report frequent use of codifiable tasks.

Table 2.7: Explaining the perceived layoff risk: task explicitness-education interactions

1979		
No/unknown education	1.814***	(.14)
Vocational school (Berufssch.)	1.665***	(.08)
Full-time vocational school (Berufsfachsch.)	1.433***	(.16)
Master crafts (Meistersch.)/Technical school (Technikersch.)	1.440**	(.24)
Health care school(Gesundheitswesensch.)	2.019**	(.72)
Civil cervants' school (Beamtenausbildung)	1.903**	(.56)
Other vocational schools	1.547*	(.40)
Vocational academy (Berufsakad.)/Technical college (FHS)	1.619*	(.44)
University	1.266	(.38)
1998/1999		
No schooling	2.054***	(.20)
Any vocational school or similar	1.525***	(.06)
Master crafts, technical school or similar	1.465***	(.15)
Technical college	1.434**	(.25)
University	1.701***	(.24)
2005/2006		
No schooling	1.400***	(.18)
Vocational training of any kind	1.288***	(.06)
Master crafts, technical school and similar	1.387***	(.17)
Technical college/University	1.507***	(.12)

Dependent variable: perceived lay-off risk; All specifications and observations same as in Table 2.6 (Models Ia, Ib and Ic). The schooling classifications differ by wave and therefore are not strictly comparable

Finally, we want to know whether the relationship between task explicitness and layoff risk differs by industry. This is an important issue as it is well evidenced that automation is not equally advanced in all industries. Automation of explicit tasks such as train driving even today has hardly any impact on labor, while automation in manufacturing should have gone a long way in substituting human effort. Additionally, the private sector may manage labor differently than the public sector. The former should react faster to possibilities for productivity enhancement than the public one.

In order to analyze the differences, we interact the industry dummies with the variable which indicates explicit tasks' performance. As a reference group we choose the employees in agriculture and mining who do not report frequent use of explicit tasks. Now we can compare the coefficients for employees in other industries who do not report frequent use of explicit tasks with those of the employees in the same industries who report frequent use of such tasks. Table 2.8 contains the results of this analysis. What we expect is that, in at least in some industries, employees who report frequent use of explicit tasks also report higher layoff risk. This is indeed the case. First, all significant odds ratios in models II are higher than 1. This is not the case with models I. Also, the odds ratios in models II are consistently higher than those in models I. Across survey waves, the significant differences between the groups with and without frequent use of explicit tasks (see the χ^2 column) are found in manufacturing, services, public administration and energy, and garbage collection.

We find no significant differences between employees who frequently perform explicit tasks and those who do not in construction, postal service, and railway and road transportation. It is beyond the scope of this study to explain these patterns. With this information we cannot discriminate whether it is the public type of (some of) these sectors or the limitation of the technology which still makes it difficult to substitute for locomotion-related and construction-related tasks that drives the results. Further research in the industry-specific patterns of technological change should provide more informative investigations on this issue.

Table 2.8: Explaining the perceived layoff risk: Task explicitness-industry interactions

Industry	Explicit=0		Explicit=1		χ^2
	Model I		Model II		
			1979		
Manufacturing	1.421***	(.18)	1.699***	(.09)	1.42
Construction	1.598***	(.24)	1.794***	(.19)	.29
Rail- and road transport	1.061	(.29)	1.228	(.35)	.08
Services	1.206	(.16)	1.626***	(.10)	3.76*
Public administration	.512***	(.09)	1.750***	(.31)	15.66***
Energy/garbage collection	.685	(.22)	2.208**	(.82)	3.38*
Post	1.144	(.29)	1.247	(.39)	.03
			1998/1999		
Manufacturing	.673**	(.13)	1.534***	(.08)	15.58***
Construction	.949	(.20)	1.458***	(.17)	2.47
Rail transportation	.461	(.28)	1.223	(.78)	.65
Services	.574***	(.11)	1.669***	(.08)	27.09***
Public administration	.278***	(.06)	1.494***	(.18)	39.8***
Energy/garbage collection	.692	(.18)	.994	(.25)	.71
Post	.737	(.20)	1.111	(.31)	.72
			2005/2006		
Manufacturing	.856	(.14)	1.298***	(.08)	5.20**
Construction	1.038	(.19)	1.346**	(.19)	.90
Services	.765*	(.12)	1.385***	(.07)	11.73***
Public administration	.470***	(.09)	1.140	(.19)	8.27***
Energy/garbage collection	.469***	(.11)	1.901**	(.49)	1.99***
Post	1.204	(.30)	1.123	(.34)	.02

Dependent variable: perceived layoff risk. All specifications and observations and explanations are same as in Table 2.6 (Models Ia, Ib and Ic).

2.7 Conclusions

Similar to other developed countries, the occupational structure of Western Germany changed in a salient way in the last few decades. These changes were not necessarily those expected by employment researchers. Earlier research expected that the employment share of occupations would increase proportionally to their job quality. This meant that better paid jobs and jobs with higher educational requirements were expected to increase their employment share at the expense of those with lower job quality. Such anticipation was later justified since many of the top paid occupations were at the same time the fastest growing ones. Nevertheless, an unexpected finding in the recent literature is that the major employment downsizing occured in the middle paid and not the worse paid occupations. The leading explanation for this observation is that new advances in technology, in particular computerization, substituted tasks that are highly codifiable. It happened that occupations with highly codifiable tasks were concentrated in the middle of the wage distribution in the period of computer proliferation. Our findings support part of the predictions outlined in this nuanced theory of skill-biased technological change.

We find that high frequency of tasks that can be explained in each and every detail (explicit tasks) correlates with higher layoff risk at the individual level. This is not necessarily the case with tasks of a repetitive nature. The positive correlation between the frequency of explicit tasks and layoff risk holds for employees with different educational levels and for labor in various broadly defined industries. The correlation is independent of the gender and age of an employee and is present in both the pre-reunification and the reunification period in Western Germany.

The reasons why labor with codifiable task content is at higher layoff risk may be multiple. For instance, both computerization of the workplace and international outsourcing of parts of the production process may result in downsizing of such labor. Although some effort is already being made to distinguish such forces (e.g., Goos, Manning, Salomons 2009), further research should be undertaken to disentangle the impact of different factors on occupational structure shifts.

Other stable and consistent findings are that the frequency of cognitive tasks such as educating, organizing and coordinating, improving processes/trying out new things, and managing are associated with lower perceived layoff risk. The relationship between service-oriented tasks such as marketing, sales/customer support, and medical/cosmetic care on one side and job security on the other is ambiguous. The growth of service jobs in the economy does not necessarily translate into their higher security.

We finally offer evidence that the decline in the price of low paid service jobs in the 1990s coincided with a period of labor supply push from manufacturing, agriculture and mining, and construction. Since the low paid service jobs require minimum training, a supply push from other sectors may explain their low job security albeit increased demand for these services.

The findings are relevant for educational and requalification policies. Education should shift the curriculum away from specialized and highly explicit knowledge and foster more general problem-solving curricula.

Chapter 3

Technology, outsourcing, and the demand for heterogeneous labor: Exploring the industry dimension

Already at the beginning of section 1.3 we explicate that the history of technological and organizational change witnessed both, innovations that were complementary to labor in carrying out explicit or routine tasks (e.g., the assembly line) and those which were complementary to labor in executing nonroutine tasks (e.g., computers). Some of these technologies were so pervasive that they resulted in economy-wide restructuring of labor. For example, given the size and the importance of the textile industry in Great Britain at that time, the changes in the skill-mix structure caused by the introduction of the labor-saving looms had nation-wide implications. Moreover, as the assembly line encountered acceptance across various manufacturing industries, it led to an increase in the demand for explicit work content at the economy level.

While some of these technologies were industry-specific (automated looms), others were economy-wide (assembly line or computers). The recent discussion on the impact of organizational and technological change has mainly focused on capturing economy-wide patterns (e.g., Geishecker 2006a; Spitz-Oener 2006; Addison et al. 2008; Baumgarten 2009; Dustmann, Ludsteck, and Schönberg 2009; Goos, Manning, and Salomons 2009). One justification for this is that consistent patterns of technological and skill changes have been found by exploring between- industry variation (e.g., Berman, Bound, and Griliches 1994; Berman, Bound, and Machin 1998; Autor, Levy, and Murnane 2003). In this article we test for the possibility that the impact of technological and organizational innovations may be industry-specific. Therefore, we adopt an empirical design that allows for technology to vary between industries while retaining the assumption that it is comparable within sectors.[1] A certain type of labor that is substitutable by technology in one industry might be unaffected by, or even complementary with, technology in some other industry if both employ qualitatively different production processes. This reasoning stems from the belief that not all technologies and organizational practices are general in the sense that they penetrate a large number of industries. Some of them may find use in only few sectors.

In the current work we will confront two possible causes of shifts in the demand for labor of different tasks: technology and outsourcing. We approximate technology by information technology (IT capital) and non-information technology (non-IT capital). However, instead of testing for economy-wide patterns, we investigate labor-technology and labor-outsourcing relations at the industry level. For that purpose we utilize a linked employer-employee panel (LIAB) of Germany, differentiated by industries for the period 2001-2005. We additionally merge the LIAB with task data from the QCS. Therefore, we can distinguish between (a) abstract labor, which captures the intensity of use of complex, problem-solving skills, (b) codifiable labor, which measures the intensity of use of (manual) tasks that are of explicit or repetitive nature, and (c) interactive labor, which reflects the intensity of tasks that require direct customer support. This dataset is then used to estimate elasticities of substitution between labor and (non-)IT capital on the one hand, and labor as well as outsourcing on the other in a translog cost function framework. With the current

[1] Given that industries are defined around common products and production processes such assumption is not far-fetched.

design we are able to account for changes in the demand for skills that are due to the occupational restructuring within plants. In other words, we can only observe skill changes that are due to labor turnover at the level of plants, disregarding skill changes that arise from the within-occupational up- or downgrading of skills.

Coming to our results, several patterns are noteworthy. First, abstract and codifiable labor appear as mutual substitutes in all industries. This means that wage increases of codifiable labor (e.g., due to union bargaining) correlate with employment boost of abstract tasks. At the same time, abstract and interactive labor always appear as mutual complements. This does not come as a surprise because plants which increase their research capacities may also face an enhanced need for marketing and other sales capabilities. Moreover, interactive and codifiable labor are mainly mutual substitutes. Furthermore, we do not find evidence of skill bias in the IT and non-IT capital; substitution effects across heterogeneous labor within industries are symmetric across labor types. However, at least in the case of IT there are pronounced inter-industry differences in the relationship between IT and labor demand in general; in some industries IT substitutes for labor of all tasks, while it complements labor in others. Non-IT capital is always a substitute for labor across industries. Nevertheless, the magnitudes of the substitution elasticities for both IT and non-IT capital are comparatively small and thus only explain a fairly small share of the changes in the demand for labor of different tasks. Finally, in industries where outsourcing significantly correlates with the demand for labor, the patterns are in line those described by Blinder (2006). Namely, the results suggest that in one third of the industries codifiable labor is at risk of outsourcing, while this is the case with abstract labor in one quarter of the sectors. The demand for interactive labor either correlates positively with outsourcing or is unaffected by it in all but one sectors.

The remainder of the chapter is organized as follows. In section 3.1 we introduce the conceptual part and formulate our expectations. Section 3.2 describes the data and the definition of variables. Section 3.3 demonstrates some basic industry-level trends. Section 3.4 explains our methodology, while our findings are discussed in section 3.5. Section 3.6 presents the various robustness checks. Section 2.7 concludes.

3.1 Tasks, technology, and outsourcing

The skill structure of developed economies changed in a remarkable way since the second half of the twentieth century. Educational upgrading was a prevalent trend and much evidence pointed toward increases in skill-premia (e.g., Goldin and Katz 2009)[2] and increases in wage inequality (e.g., Autor, Katz, and Kearney 2008; Dustmann, Ludsteck, and Schönberg 2009). Within the last three decades numerous studies investigated the sources of change in the labor structure. The majority of these assumed the *level* of human capital as measured by educational attainment to be the most relevant dimension of human capital (e.g., Goldin and Katz 1996 and 2009; Acemoglu 1998 and 2003; Bresnahan, Brynjnolfsson, and Hitt 2002). More recent literature, starting with studies such as those by Autor, Levy, and Murnane (2003) and Blinder (2006), argued that it is rather the *type* and not the *level* of human capital that encompasses most useful information in explaining the causes of the recent trend toward skill upgrading.

Two of the dominant theories that aspire to explain the skill upgrading in the recent decades is the skill-biased technological change theory (see Katz and Autor 1999 for a review of earlier studies) and the opening up of trade to world markets (see Grossmann and Rossi-Hansberg 2008 for a theory of international tasks trade).

As already explained in sections 1.3 and 2.2, Autor, Levy, and Murnane (2003) relate the changes in the labor structure since the 1960s to the proliferation of computers at the workplace. However, unlike much of the previous studies, they ask the critical question: what kind of tasks do computers execute that substitute or complement tasks carried out by humans? Therefore, instead of using the conventional labor group distinctions (low-skilled, medium-skilled, and high-skilled; production and non-production workers; or blue-collar and white-collar), they propose a measurement of tasks that provides an intuitive and testable explanation of the causal relationship between the introduction of new technologies and the demand for heterogeneous labor. Here we briefly summarize the basic argument again. Computers

[2] See Lemieux (2006) for a critique and evidence against increasing skill-premia in the U.S..

substitute for routine manual and cognitive tasks, while complementing nonroutine manual and cognitive ones. This is because routine tasks embody explicit knowledge that can relatively easily be programmed, which is not the case with nonroutine tasks. Moreover, a rise, both qualitatively and quantitatively in the supply of codifiable tasks increases the marginal productivity of employees who make extensive use of nonroutine tasks (such as problem-solving and coordination) and who use routine work output as their work input (Autor, Levy, and Murnane 2003, p. 1285).

However, computers developed in different forms. The personal computers, mainly substituting for cognitive routine tasks such as calculus, proliferated in all industries, while computerized numerical control (CNC), which mainly substitutes for manual repetitive tasks, retains its presence in a limited number of manufacturing industries. Furthermore, certain technologies such as the automatic cashier or the automated teller machine (ATM) in retail and banking substitute for repetitive tasks and result in a reduction of tasks that entail direct contact with customers (interactive tasks). There are also code-based technologies such as loyalty card systems mainly present in retail stores where there is no reason to expect a bias toward certain labor type. Hence it is quite plausible to expect that industries may exhibit pronounced idiosyncrasies in the labor-IT capital relations.

As explained in section 1.3, the period of IT proliferation coincided with a period of rapid increases in the international trade. According to Grossman and Rossi-Hansberg (2008), a distinct feature of modern trade is that it not only includes *goods* but also *tasks*.

> "Revolutionary advances in transportation and communications technology have weakened the link between labor specialization and geographic concentration, making it increasingly viable to separate tasks in time and space. When instructions can be delivered instantaneously, components and unfinished goods can be moved quickly and cheaply, and the output of many tasks can be conveyed electronically, firms can take advantage of factor cost disparities in different countries without sacrificing the gains from specialization." (Grossman and Rossi-Hansberg 2008, p. 1978)

While Grossman and Rossi-Hansberg (2008) leave the question of which types of tasks are outsourceable open for discussion, Blinder (2006, 2009) offers a theory of offshorability. Blinder (2006) argues that the offshorability of an occupation is neither correlated with its level of education nor with its median wage. What is important, he argues, is whether a service is delivered personally or impersonally (see section 2.2 on page 26).

Both the theory of technological change and the theory of international outsourcing provide testable hypotheses about the causes behind the recent changes in task/skill mix in developed countries. Following Autor, Levy, and Murnane (2003), the labor-IT capital relationships should be such that (a) routine (both cognitive and manual) tasks appear as technological substitutes, while (b) nonroutine manual and cognitive tasks are technological complements. Blinder predicts that most vulnerable to international outsourcing are routine (codifiable) tasks and abstract tasks that do not require personal delivery to customers. Interactive tasks, on the other hand, should show low outsourcing propensity.[3]

Having derived the main expectations that guide our empirical analysis below, we conclude the theoretical considerations by stressing that the outsourcing-labor relationship is two-dimensional. Differences in firms' outsourcing behavior across industries may either stem from the inter-industrial variation in production practices or from the stage of the outsourcing process. For example, in motor vehicles production firms are likely to outsource qualitatively different parts of the production process than those in professional business services. The former may primarily outsource product assembly, which is codifiable task intensive, while the latter may outsource programming and statistical analysis services, mainly affecting abstract labor. Yet over time the same industry may change the type of labor being outsourced. There is evidence that industries outsource routine tasks first and as time progresses switch over to outsource more complex firm functions as well (see e.g., Pfannenstein and Tsai 2004 for the U.S. IT industry and Maskell et al. 2007 for Danish international

[3]Goos, Manning, and Salomons (2009) provide an empirical test of the theories of Autor, Levy, and Murnane (2003) and Blinder (2009) at the economy-wide level.

firms). For example, having outsourced production parts internationally from the middle of the 1990s on, the German automobile industry may have created new business opportunities which, in a more advanced stage of industry outsourcing, attract labor to foreign countries that makes intense use of abstract tasks.

3.2 Data and task measures

3.2.1 Qualification and Career Survey

The Qualification and Career Survey was already described in section 2.3. [4] For the purpose of this study we use the 1998/99 survey. This is because the relevant establishment-level information for the linked employer-employee panel is first available in 2001 and this is the survey that most closely reflects the task composition of occupations at the initial period of our analysis. A list of variables used from this survey and their definitions can be found in appendix B, Table B1. We focused on variables that we can consistently compare over time, in particular those that we can compare with past surveys. We measure task intensities at the level of occupations. The fact that our data come from two different sources requires that we measure the task intensities at the level of occupations[5]. The reporting of the employees' occupation is not one of the information categories that employers must highly accurately report, therefore, the IAB recommends an occupational aggregation of that data between the 2- and 3-digit level, which results in 120 different occupations. Out of these we drop the public administration jobs, as well as family assistants, interns and unpaid trainees. The final classification embraces 115 different occupations.

We try to measure three task dimensions: (1) abstract, (2) codifiable, and (3) interactive. The abstract dimension corresponds with the nonroutine cognitive one in

[4] Previous uses of this survey are by DiNardo and Pischke (1997), Spitz-Oener (2006), Dustmann, Ludsteck, and Schönberg (2009), and Gathmann and Schönberg (2010).

[5] Some of the above-mentioned studies measure these tasks at the level of individuals (Spitz-Oener 2006), others at the level of occupations (Goos, Manning, and Salomons 2009).

ALM and the abstract one in Goos, Manning, and Salomons (2009); the interactive dimension corresponds to the service dimension in Goos, Manning, and Salomons (2009). The codifiable dimension is designed to capture two characteristics of knowledge: its repetitiveness and its explicitness. Hence it is more general than the routine measure used in previous studies.[6]

The question that captures the codifiable dimension is already explained in section 2.3, but for clarity we explain it again here. The question that we use as a measure of explicitness of tasks asks: how often does it happen that you are being *instructed about the work-process in every detail* at your daily work? The answer is given on a likert scale: practically always, often, from time to time, seldom, practically never. We know that from a theoretical point of view the explicitness of a task is a better appoximation of codifiability than the repetitiveness of tasks. This is also confirmed in chapter 2 where we show that only the explicitness and not the repetitiveness of tasks gives a stable and consistent prediction about the job stabilitiy of individuals. Therefore, the measure of task repetitiveness is used mainly for robustness checks.

As explained in chapter 2, unlike the case of the codifiable dimension, where we have questions asking precisely the frequency of use of repetitive and explicit tasks, it is more difficult to separate interactive and abstract tasks. Instead of arbitrarily defining which tasks belong to one of these categories we again adopt factor analysis appoach in order to check whether subsets of variables are loading on common factors. Appendix B contains the factor loadings and the relevant characteristics of the resulting factors.

The main result of the factor analysis is identification of two dimensions (see Table B6 in appendix B). Variables such as marketing and public relations, management, process improvement, research, mathematics and statistics, usage of foreign languages, and negotiation load high on the first factor. These are tasks that require complex

[6] Previous work that uses the task-based approach in order to caputure relevant dimensions of the work content of jobs distinguishes three to four groups of tasks. ALM, as well as Spitz-Oener (2006) distinguish between routine cognitive, routine manual, nonroutine cognitive, and nonroutine manual. Goos, Manning, and Salomons (2009) differentiate abstract, routine, and service tasks. The routine dimension in this case captures both the routine cognitive and the routine manual tasks.

and abstract thinking and problem-solving. Groups of occupations that score highest on this dimension are engineers, managers and entrepreneurs, technicians and scientists. We call this factor *abstract dimension*. The second factor loads on two variables: medicical knowledge and taking care of people. These are tasks that involve direct and intense contact with customers. Therefore, we refer to this factor as *interactive dimension*. The measures of abstract and the interactive skills are by construction orthogonal to each other, while the measures of explicit and routine tasks are not.

Since the occupation-specific task quantities that we use in the regression analysis are measured at one time point, a major limitation of the current empirical design is that we can only observe task changes that result from shifts in plants' occupational structure but not those changes that stem from the task up- or downgrading within same occupations over time.

3.2.2 Linked Employer-Employee Panel

The Linked Employer-Employee Panel (LIAB) is a dataset of up to 16,000 establishments per year matched with the employment histories of their employees for both Eastern and Western Germany in the period 1993-2008. The plant-level information comes from an annual survey of German establishments, the Establishment Panel, administrated by the Institute for Employment Research (IAB), while the individual level data comes from the German Social Security notifications. Detailed description of this dataset is given by Jacobebbingshaus (2008). For the purpose of our analysis we use a subset of this dataset. We select twelve large industries at the 2-digit industry level: chemicals; plastic and rubber; ceramics, glass, and bricks; iron and steel; metal production; vehicle manufacturing; general and special purpose machinery; electrical equipment; control, optical instruments and watches; construction; wholesale; and retail. The choice of the industries was dictated by the sample size and by the information availability on the relevant variables.[7] On the individual side, both males and females are considered. Information on the share

[7]For example, many of the service sectors do not report sales in monetary terms and for these we cannot use the translog cost function specification where measure of output is necessary.

of information technology (IT) investments in the total investments is present since 2001 (financial year 2000) in the LIAB, and, at the point of the dataset building, it was available on annual basis until 2005 (financial year 2004). The data reported at the establishment level always refers to the previous financial year. Therefore, the actual period of observation are the financial years 2000-2004. On the side of the individuals, labor data is reported each year at 30$^{\text{th}}$of June. Therefore, the labor (task) quantity and price information by construction succeeds the (non-) IT capital flow and outsourcing reportings by at least six months.

The IT investments are reported as a share of the total investments in the Establishment Panel. From the monetary value of the total investments we derive the monetary value of the annual IT investments of each establishment. Non-IT investments are accordingly the difference between total investments and IT investments. We then estimate stocks of IT and non-IT capital on the basis of investment data employing the Perpetual Inventory Method (PIM) with geometric depreciation profiles. These are the measures of IT and non-IT capital that we employ in the regression analysis. Depreciation rates differ by asset and industry.[8]Output is measured by the monetary value of sales. Outsourcing is a dummy variable. Establishments are asked to report whether they have outsourced a unit in the previous financial year. There is no information on whether outsourcing has been made to another sector or to a foreign country in the observed period.[9] We deflate the monetary values of sales, (non-) IT capital, and labor prices with industry-specific deflators provided by the German Federal Statistical Office and the German Council of Economic Experts.

For labor we have information about the number of employees by plant at each time point. For every employee, beside other information, we also have very reliable daily wage data.[10]This individual data comes from the employment histories of employees that are part of the German system of social security. Besides wages we also have

[8]The details of capital stock construction are relegated to appendix B.

[9]Starting in 2006 establishments are also asked to report whether they outsource at home or to a foreign country.

[10]The daily wage data is right censored.Therefore, we employ wage imputation technique proposed by Gartner (2006) for the wage values that are missing due to censoring.

information about the occupations of each employee. This allows us to merge the task data from the QCS on occupational level with the LIAB.

The labor input can either be measured in terms of number of employees of different types (labor quantity approach) or quantity of tasks of different types (task quantity approach). Two obvious advantages of the labor quantity approach are that we have a natural labor unit-employee number of certain type, and that we can easily attach a price to each unit. This approach has a number of disadvantages, however. First, all occupations within one group are considered to be identical. Therefore, employing five engineers is treated same as employing five engineering technicians. Second, a number of occupations would have to be omitted because they score low on all three dimensions. Third, and perhaps most important is that we would not make a full usage of the information we have at hand. For example, a plant that does not employ any interactive-tasks-dominated labor will still employ some interactive tasks content that is embodied in the labor task portfolio. This information would get lost if we used the labor quantity approach. Given these drawbacks, we choose the tas -quantity approach.

For this purpose we use the two factors and the explicit tasks measure described earlier in this section and appendix B. In order to make the measures of tasks comparable among each other, we represent them in terms of their position on the occupational task distribution. In other words, they are measured in percentiles. For example, a machine engineer in our approach scores at the 98$^{\text{th}}$ percentile of the abstract tasks distribution, at the 9$^{\text{th}}$ percentile of the routine tasks distribution, and at the 2$^{\text{nd}}$ percentile of the interactive tasks distribution. The respective percentiles for a plastics' processor are 21$^{\text{st}}$, 96$^{\text{th}}$, and 8$^{\text{th}}$. Therefore, a plant employing one machine engineer and one plastics' processor will have .98+.21=1.19 units of abstract task quantity, .09+.96=1.15 units of routine tasks quantity, and .02+.08=.1 unit of interactive tasks quantity. The price per unit of labor is defined as follows: $P_i = \sum_{j=1}^{n}(p_i * t_{ij}/\sum_{i} t_{ij})$ where P is the establishment-level price of a task type, p is the individual-level wage, t represents the type of task, $j = 1, ..., n$ is the employee counter and $i = abstract, codifiable, interactive$. Think of a plant with two employees, one machine engineer and one plastics processor; the engineer earns 100 euro daily wage and the plastics' processor earns 50. The price of abstract labor for this plant will be determined as follows: 100*.98/(.98+.09+.02)+50*.21/(.21+.96+.08)=89.9+8.45=98.38 Accordingly, the prices for codifiable and interactive labor will be 46.97 and 3.24, respectively.

Although the prices of task quantities are indirectly derived, they have desirable properties. First, if occupations with high intensity of abstract tasks are also highly payed, this will be reflected in the indirect prices. Second, smaller quantities of certain tasks correlate with small total pay. Finally, by construction the task expenditures at the establishment level sum up to 100 percent of the wage bill.

3.2.3 The final sample

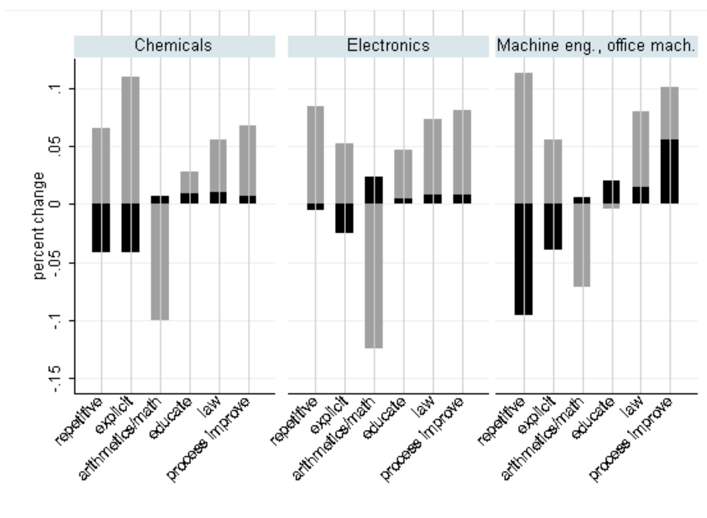
In order to ensure better reliability of our data, following Addison et al. (2008) we excluded from the sample those matches between the individual and the establishment data where the employment count based on the individual data was at least 20 percent larger or smaller than the reported one in the Establishment panel.[11] The final sample is an unbalanced panel with 7513 observations over a period of five years. This sample is divided among 12 industries, the smallest of which is electrical equipment manufacturing (314 observations) and the largest one is construction (1727 observations). Despite the non-negligible reduction of the industry-level subsamples due to missing values, the construction of the capital stocks and the exclusion of the mismatches, we manage to obtain samples that incude entablishments of all sizes, both in terms of employment and in terms of output. Additional descriptive statistics can be found in appendix B.

3.3 Changes in the demand for tasks

The main interest of this study is to see whether there are deviations from the overarching trends in skill up- and down-grading (see section 2.5 in chapter 2) when we look at separate industries. Figure 3.1 presents the results of a shift-share analysis of occupation-level task changes estimated separately for 9 industries. A striking observation is that when looking at the within changes across industries for same tasks remarkable similarities occur. Namely, people in all industries report higher use of repetitive and explicit tasks, lower use of arithmetic, math and statistics and mainly higher use of educating, law and process improvement. Nevertheless, when looking at the between occupational changes, we see notable discrepancies. Figure 3.1(a) shows a group of industries (chemicals, electronics, and machine engineering

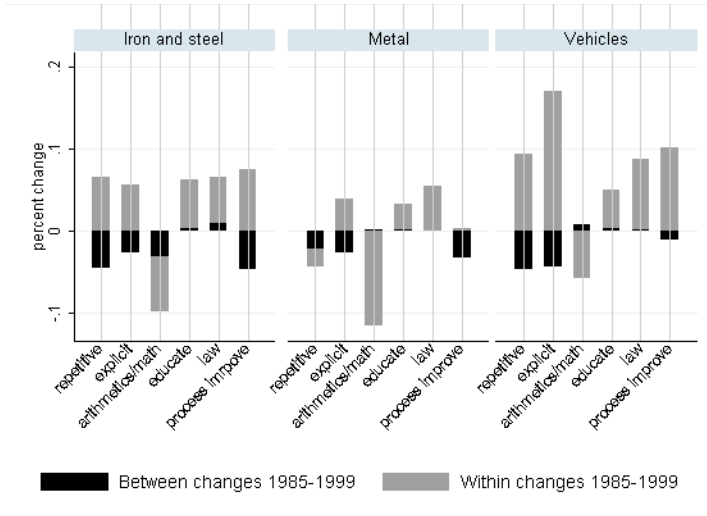
[11] Certain mismatch in these reportings should be tolerated for at least two reasons. First, the reporting periods of the establisment survey and the individual data are several months apart. Second, we only work with employment subject to social security. While for plants it may be easy to know the total number of employees, they are less precise when reporting the number of employees subject to social security. Moreover, if the misreporting would stem from the side of the individual data, there is no reason to believe that some type of selectivity takes place.

and office machinery) where occupations which perform codifiable tasks decreased their employment share, while occupations which perform other than codifiable tasks expanded. In Figure 3.1(b) we observe a group of industries that decreased the presence of occupations who often perform codifiable tasks, but also decreased the employment of those who perform tasks such as process improvement. Finally, in Figure 3.1(c) we see industries where the occupations performing codifiable tasks gained in employment. Therefore, from this section we can conclude that while the within-occupational task changes are remarkably similar across industries, the between-occupational changes vary notably. As a next step we investigate whether these departing trends can be explained by differences in the technology-labor and outsourcing-labor relations across sectors[12].

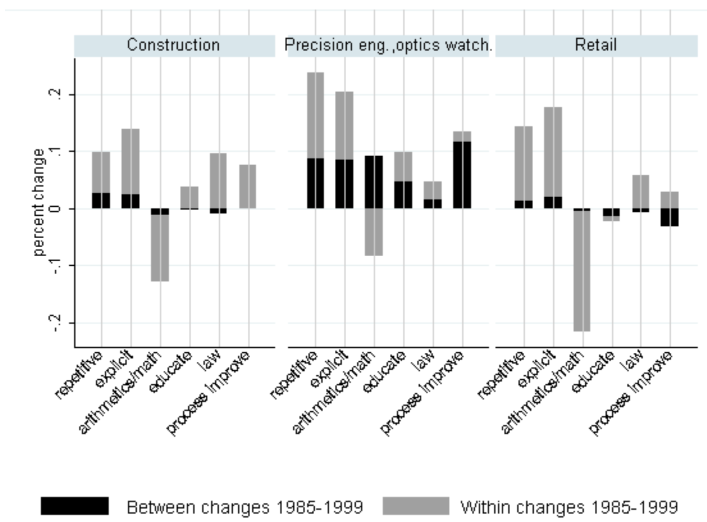


(a)

[12]Please note that the time period for which we present these descriptive results does not overlap with the time period for which we undertake the econometric analysis. This is due to the discontinuity in the industrial classification in the QCS which does not allow us to compare industries between the 1998/1999 wave and the 2005/2006 wave.


Iron and steel
Metal
Vehicles
percent change
.2
.1
0
-.1
repetitive
explicit
arithmetics/math
educate
law
process improve
Between changes 1985-1999
Within changes 1985-1999

(b)


Construction
Precision eng.,optics watch.
Retail
percent change
.2
.1
0
-.1
-.2
repetitive
explicit
arithmetics/math
educate
law
process improve
Between changes 1985-1999
Within changes 1985-1999

(c)

Figure 3.1: Between- and within-occupational task changes by industry (1985-1999)
Source: QCS 1985, 1991/1992 and 1998/1999. Note: Changes in arithmetic/math/statistics are estimated for the period 1992-1999. The industrial classifications in the 1979 and 2005/2006 waves differ from those of the 1985, 1991/1992 and 1998/1999 and are therefore not considered.

3.4 Theoretical model and empirical specification

The estimation of the demand for heterogeneous labor is based on a translog cost function that can be envisaged as a second-order Taylor's series approximation in logarithms to an arbitrary (twice-differentiable) cost function. While the majority of studies on labor substitutability distinguish between skilled and unskilled employees[13], and sometimes differentiates these two groups further by gender and type of employment (Freier and Steiner 2007), the focus of our study is on labor heterogeneity with respect to tasks. Thus, following the discussion in the previous section, we consider a cost function specification that incorporates task-differentiated labor as variable input. Since we are interested in the direction and the extent of substitution relations between labor of different tasks and a plant's technological base underlying production, we include capital and outsourcing in our cost function framework. We have information on the composition of plant's investment expenditures, allowing us to construct capital stocks of IT and non-IT, respectively.[14] We treat (non-)IT

[13]Examples are Berman, Bound, and Griliches (1994), Betts (1997), and Adams (1999). See Hamermesh (1993) for a detailed survey.

[14]A number of previous studies estimating substitution patterns on the labor market insert investments directly into the cost function (Van Reenen 1997; Addison et al. 2008). The implicit assumption this approach entails is that replacement investments properly reflect necessary depreciation and are therefore proportional to the unknown capital stock (Mueller 2008). However, whether or not (replacement) investments are proportional to the true capital stock cannot be verified by data (Mueller 2008). Moreover, missing values or zero investments in one year would cause a capital stock measure of zero for that year, which obviously is implausible. In order to avoid these drawbacks we construct absolute values of capital stock.

capital stocks and outsourcing as quasi fixed, implying that producers cannot adjust freely in response to relative price changes in the short run.[15] Justifications for the quasi-fixity of the capital variables and outsourcing are the presence of institutional constraints as well as adjustment costs for these factors that are beyond the control of an individual plant.[16] Specifiying the cost function in the quasi-fixed form has the additional virtue that each variable assumed to be quasi fixed enters with its quantity rather than with its price. According to Berman, Bound, and Griliches (1994), there are no reliable price deflators available for capital, which even the more holds for IT investment and outsourcing (Aguirregabiria and Alonso-Borrego 2001). Furthermore, observed capital quantities can often be seen as closer proxies to user cost of capital than price measures (Muendler and Becker 2009).

With (non-)IT capital stocks and outsourcing being fixed at levels other than their long-run equilibrium values, the goal of the plant is to minimize the cost of variable inputs conditional on a given quantity of the quasi-fixed factors. It is thus appropriate to specify a *variable* cost function that reads in its general form:

$$VC = f(P_A, P_C, P_I, Y, K, IT, OUT), \tag{3.1}$$

where three variable inputs are considered, abstract labor (L_A), codifiable labor (L_C), and interactive labor (L_I), which appear in the cost function through their prices, P_A, P_C, and P_I, respectively; output is denoted by Y, while K, IT, and OUT represent the quantity of the quasi-fixed inputs non-IT capital, IT capital, and outsourcing.

For purposes of estimation we must employ a specific functional form for equation 3.1. We require it to be sufficiently flexible to allow the data to display complementarity as

[15]Most of previous work investigating changes in the employment strcuture in the context of a translog cost function assumed capital to be a quasi-fixed input (Bartel and Lichtenberg 1987; Slaughter 1995; Adams 1999; Hollanders and ter Weel 2002; Becker et al. 2005; Muendler and Becker 2009).

[16]Notice that we do not specify a dynamic labor demand model (Berndt et al. 1981; Good et al. 1996; Morrison Paul and Siegel 2001), because the assumptions about adjustment cost in these models are rather crude and questionable (Hamermesh 1993; Kölling and Schank 2002). Moreover, as elaborated below, we neither impose homotheticity nor constant returns to scale on the cost function. We would have had to sacrifice this degree of flexibility if we wanted to explicitely model the adjustment process of the quasi-fixed factors (Baltagi and Rich 2005).

well as substitutability between inputs, which excludes, for example, Cobb-Douglas or constant elasticity of substitution specifications. We choose a translog variable cost function to approximate equation 3.1, because it places no a priori restrictions on the partial elasticities of substitution (Christensen et al. 1971 and 1973; Brown and Christensen 1981).[17] The translog variable cost function is written as:[18]

[17]A variety of functional forms allow for complex substitution patterns (see Chambers 1988 for a comprehensive overview), with translog and generalized Leontief (Diewert 1971) specifications being most prominent among these. We favor a translog over a generalized Leontief cost function since the former's dimensionality requirements are considerably leaner (Muendler and Becker 2009). In addition, the Monte Carlo analysis of Guilkey et al. (1983) finds that the translog outperforms the generalized Leontief in approximating the true data-generating process for a wide range of substitution elasticties.

[18]Since linear homogeneity in prices is imposed (see below), we can write the regressors in equation (2) as logarithms of the price ratios (Berndt and Wood, 1975). Notice further that outsourcing is a binary variable, taking only values of either zero or one, which in that case prevents us from using a logarithmic specification.

$$
\begin{aligned}
\ln VC = \quad & \alpha_0 + \alpha_A \ln \tfrac{P_A}{P_I} + \alpha_C \ln \tfrac{P_C}{P_I} + \ln P_I + \alpha_Y \ln Y \\
& + \alpha_K \ln K + \alpha_{IT} \ln IT + \alpha_{OUT} * OUT + \tfrac{1}{2}\beta_{A,A} \ln^2 \tfrac{P_A}{P_I} \\
& + \tfrac{1}{2}\beta_{C,C} \ln^2 \tfrac{P_C}{P_I} + \tfrac{1}{2}\beta_{Y,Y} \ln^2 Y + \tfrac{1}{2}\beta_{K,K} \ln^2 K \\
& + \tfrac{1}{2}\beta_{IT,IT} \ln^2 IT + \beta_{A,C} \ln \tfrac{P_A}{P_I} \ln \tfrac{P_C}{P_I} + \beta_{A,Y} \ln \tfrac{P_A}{P_I} \ln Y \\
& + \beta_{A,K} \ln \tfrac{P_A}{P_I} \ln K + \beta_{A,IT} \ln \tfrac{P_A}{P_I} \ln IT + \beta_{A,OUT} \ln \tfrac{P_A}{P_I} * OUT \\
& + \beta_{C,Y} \ln \tfrac{P_C}{P_I} \ln Y + \beta_{C,K} \ln \tfrac{P_C}{P_I} \ln K + \beta_{C,IT} \ln \tfrac{P_C}{P_I} \ln IT \\
& + \beta_{C,OUT} \ln \tfrac{P_C}{P_I} * OUT + \beta_{Y,K} \ln Y \ln K + \beta_{Y,IT} \ln Y \ln IT \\
& + \beta_{Y,OUT} \ln Y * OUT + \beta_{K,IT} \ln K \ln IT \\
& + \beta_{K,OUT} \ln K * OUT + \beta_{IT,OUT} \ln IT * OUT.
\end{aligned}
\tag{3.2}
$$

A well-behaved (variable) cost function must be homogeneous of degree 1 in factor prices, given output, which requires that $\sum_j \alpha_j = 1$ and that $\sum_j \beta_{j,n} = \sum_n \beta_{n,j} = \sum_j \beta_{j,Y} = \sum_j \beta_{j,K} = \sum_j \beta_{j,IT} = \sum_j \beta_{j,OUT} = 0$ for all $j, n = A, C, I$. For notational convenience we avoid the indexes which point out the plant and year specificity. However, all data points are plant- and year-specific. Although the arguments of equation 3.1 are available at the plant level, to give our results an interpretable meaning we assume that the production technology of each plant within a (broadly defined) industry is identical. Moreover, we allow for industry-specific scale economies by not restricting the variable cost function 3.1 to exhibit constant returns to scale.

Cost-minimizing demand equations for variable inputs are obtained by logarithmically differentiating equation 3.2 with respect to variable input prices, which, when employing Shephard's Lemma, gives the share of overall labor cost attributable to each factor j:

$$
\begin{aligned}
S_A = \quad & \alpha_A + \beta_{A,A} \ln \tfrac{P_A}{P_I} + \beta_{A,C} \ln \tfrac{P_C}{P_I} + \beta_{A,Y} \ln Y \\
& + \beta_{A,K} \ln K + \ln \beta_{A,IT} \ln IT + \beta_{A,OUT} * OUT, \\
S_C = \quad & \alpha_C + \beta_{C,C} \ln \tfrac{P_C}{P_I} + \beta_{A,C} \ln \tfrac{P_A}{P_I} + \beta_{C,Y} \ln Y + \\
& + \beta_{C,K} \ln K + \ln \beta_{C,IT} \ln IT + \beta_{C,OUT} * OUT, \\
S_I = \quad & 1 - S_A - S_C,
\end{aligned}
\tag{3.3}
$$

where $S_j \equiv P_j L_j / VC$ denotes the share of cost of labor of task type j ($j = A, C, I$) in total labor cost $\left(VC = \sum_j P_j L_j\right)$, from which follows that $\sum_j S_j = 1$ holds.[19]

Equations (3.2) and (3.3) summarize the full range of input substitution patterns of the establishment. The coefficients capture the partial effect of the exogenous variables on the cost share of labor of skill type j. The signs of these parameters, however, do not immediately indicate the plant's substitution behavior. We therefore construct labor demand elasticties from coefficient estimates in equations (3.2) and (3.3) and mean cost shares. These elasticities quantify the response (in percentages) of labor demand for task type j to permanent changes (in percentages) in prices, output, (non-) IT capital, and outsourcing, respectively, while all other factor prices and quasi-fixed input quantities are fixed.[20] The labor demand elasticties with respect to task prices, ε_{L_j,P_n}, are obtained as:

[19] Notice that input factor demands in (3) are to be interpreted as conditional factor demands (for a given output level), in contrast with ordinary factor demands which result from the profit maximization problem. The main difference between the primal (profit maximization) and the dual (cost minimization) specification is that price effects in conditional demands capture only pure substitution effects, whereas price effects in ordinary demands also capture the effect on the optimal output level.

[20] For the dichotomous outsourcing variable, we obtain a semi-elasticity measuring the percental change in labor demand when outsourcing occurs.

$$\varepsilon_{L_j,P_n} = \frac{\delta S_j/\delta \ln P_n}{S_j} + S_n - \delta_{j,n}, \tag{3.4}$$

where $j, n = A, C, I$, and $\delta_{j,n} = 1$ if $j = n$, and 0 otherwise.[21] Moreover, the labor demand elasticities with respect to output are calculated as:

$$\varepsilon_{L_j,Y} = \frac{\delta S_j/\delta \ln Y}{S_j} + \varepsilon_{VC,Y}, \tag{3.5}$$

where $j = A, C, I$, and $\varepsilon_{VC,Y} = \delta \ln VC/\delta \ln Y$. Elasticties with respect to the other variables of interest follow analogously, with $\varepsilon_{L_j,OUT}$ to be interpreted as a semi-elasticity.

We characterize the structure of technology in German manufacturing and services in the period 2001-2005 by estimating labor cost and share equations given by equations (3.2) and (3.3) for broadly defined industries. Three remarks are worth making about our empirical strategy before describing it in more detail below. First, a disturbing feature of equation (3.3) is that prices of task-differentiated labor are directly involved in the construction of the dependent variable, inducing a correlation between the dependent variable (cost share) and the exogenous variables. Therefore, following Muendler and Becker (2009), we transform equation (3.3) into a system of labor demand functions, in which labor prices only appear as regressors, by multiplying both sides of each share equation in (3.3) with the observation-specific scalars VC/P_j $(j = A, C, I)$.[22] Second, for empirical estimation of the cost and demand functions we need to specify a stochastic framework. We append the system by an additive disturbance term, and assume that the resulting disturbance vector is independently and identically multivariate normally distributed with mean vector zero and a constant, non-singular covariance matrix. Third, since the labor cost shares

[21] Our focus on demand elasticities deliberately contrasts with the empirical studies in the literature, which typically report Allen partial elasticities of substitution (Frondel and Schmidt 2003). According to Chambers (1988), since Allen elasticities can only be interpreted meaningfully in terms of demand elasticities, reporting the former rather than the latter just reduces transparency.

[22] Notice that the linear transformation of cost shares into labor demand equations does not affect the elasticity calculations above.

in (3.3). always sum to 1, the sum of disturbances across the three equations is 0 at each observation. Since only $n-1$ of the share equations in (3.3) are linearly independent, we arbitrarily drop the interactive labor share equation in the estimation procedure. Parameter estimates of the omitted equation can be obtained by working backward from the adding-up restrictions ensuring linear homogeneity in labor prices. As discussed in Barten (1969), Berndt (1990), and Morrison Paul (1999), the estimation results are invariant to the choice of the equation to be dropped, as long as a maximum likelihood or an iterative Zellner (seemingly unrelated) estimation procedure is employed.

In light of the discussion above, we estimate a three-equation system comprised of the cost equation (3.2) and the transformed demand functions for abstract and codifiable labor in (3.3) by iteratiing Zellner's (1962) seemingly unrelated regression (SUR) over the estimated disturbance covariance matrix until the estimates converge. The system estimation takes into account that residuals across equations may be correlated due to contemporaneous labor demand choices by plants. Both cross-equation symmetry for internal consistency of the model and linear homogeneity in labor prices contingent on the underlying production theory are imposed through constraints. Since it is unlikely that the error terms in our system of equations are uncorrelated with other right-hand-side variables, controlling for fixed effects is important. Some plants may have capable managers who employ both top quality employees (mainly performing, say, abstract tasks) and information technology. Such firm-specific performance advantage may also cause demand for different tasks to expand simultaneously, which would suggest a bias of estimated labor demand elasticities toward complementarity (Aguirregabiria and Alonso-Borrego 2001; Muendler and Becker 2009). To sweep out any unobserved (and time-invariant) plant heterogeneity, we apply the within transformation to the three-equation system represented by equations (3.2) and (3.3). Standard errors for our elasticity estimates are computed by using the "delta" method.[23]

[23]The elasticities are calculated as combinations of first and second derivatives of equations (2) and (3), evaluated at the sample means. Thus, each elasticity depends not only on the data, but also on a combination of parameter estimates, each with its own standard error. The "delta" method

Since we are looking at the establishment level, it may be reasonable to maintain the assumption that prices for task-differentiated labor are exogenous to individual firms or plants (Berndt and Wood 1975; Berndt 1990). Following the recent discussion by Muendler and Becker (2009), regarding firms as price takers in the labor market seems to be especially justifiable in the case of Germany, because firms face bargained wage schedules resulting from industry-specific collective bargaining. Strong German labor market institutions arguably make market forces less critical in determining wage movements. In addition to that, there exists an implicit minimum wage in Germany given by the high level of means-tested welfare benefits as compared to other OECD countries (e.g., Steiner and Wrohlich 2005).[24] These institutional limits to how far the wages can fall corrobate to some extent the assumption of a fixed market wage, in particular for employees in low-paying jobs. On the other hand, it is difficult to argue that the downward inlexibility of German wages is relevant for labor whose supply is rather inelastic (e.g., university graduates). Under the assumptions that these employees are relatively mobile and know approximately the market value of their labor services, preventing them from accepting positions that pay them less, it is not too implausible to also treat high-paying labor prices as being to some extent exogenous to plants.

3.5 Findings and discussion

Tables 3.1 and 3.2 present the elasticities of substitution calculated by using the coefficient estimates from the system of cost and demand functions as set forth by equations (3.2) and (3.3) for each of the twelve industries. The elasticities measure the percentage responses of demand for labor/tasks to a one percent change in either the price of a variable input or the quantity of a quasi-fixed input by industry.[25] *Elapa, Elcpc,* and *Elipi* indicate the own-price substitution elasticities of abstract,

allows a combined standard error to be computed for these expressions.

[24] In a few industries even statutory minimum wages prevail, for instance since 1997 in the construction industry and since 2007 in the building cleaning industry, both due to the Employee Sending Act (Arbeitnehmer-Entsendegesetz).

[25] In the case of outsourcing, the respective elasticities inform about the percentage change in labor demand in the presence of outsourcing.

codifiable and interactive labor, while *Elapc, Elapi, Elcpi,* and their corresponding counterparts represent the set of cross-price substitution elasticities. Because of imposed symmetry of price coefficients trough constraints on the translog regression, *Elapc* and *Elcpa* (*Elapi* and *Elipa*, *Elcpi* and *Elipc*) have the same sign but are not necessarily of the same magnitude. The terms *ElaIT (ElcIT, EliIT), ElaOUT (ElcOUT, EliOUT),* and *ElaCapital (ElcCapital, EliCapital)* report the reaction of abstract (codifiable, interactive) labor when the values of IT capital, outsourcing, or non-IT capital change.[26]

3.5.1 Price elasticities

Table 3.1 presents the price elacticities results. One common pattern is that own-price elasticities, when significant, are always negative, as production theory requires.[27] A negative own-price elasticity means that labor-saving practices are stimulated within a plant if the price of labor increases. For example, in the glass, ceramics, and bricks industry, a one-percent increase in the price of abstract labor is associated with a .47 percent drop in its demand; a one-percent increase in the price of codifiable labor corresponds to a .29 percent decrease in demand; and a one-percent increase in the price of interactive labor relates to a .55 percent demand decrease. In relative terms this suggests that if prices of all three types of labor increase by one percent, interactive labor will be most negatively affected, followed by codifiable, and then by abstract labor. In general, the impact of own-price changes on labor demand is most pronounced for interactive labor; in ten out of twelve industries, the own-price elasticity of interactive labor is higher in magnitude than the respective elasticities of abstract and codifiable labor.[28] This finding is not surprising given

[26]Since elasticties with respect to output are not in the focus of this study, we do not report them in the tables. Notice, however, that we find strong support in favor of increasing returns to scale across all twelve industries. This finding suggests that studies of German manufacturing and service industries should avoid using simple production functions such as constant elasticity of substitution (CES). In particular, if homotheticity or constant returns to scale are incorrectly imposed, movements along nonlinear expansion paths might be incorrectly explained as biased technical change (Betts 1997).

[27]The only exception is interactive labor in the plastic and rubber industry. One possible reason for this result is that demand for codifiable labor exceeded its supply in our period of observation.

[28]The only exceptions are the two service industries in our sample, retail and wholesale, both of

that many of the interactive-labor intensive occupations require little or no training. As such, interactive labor can often be relatively easily acquired and replaced. Unlike many interactive tasks, codifiable tasks frequently require certain training and dexterity that cannot be immediately achieved. This should be even more the case with abstract labor. However, we observe only in six out of twelve industries that the response to own-price changes in codifiable labor is stronger than in abstract labor. These price effects may to some extent reflect the influence of still strong unions (e.g., IG Metall in iron and steel manufacturing; metal production; motor vehicles as well as IG Bau in glass, ceramics, and bricks; construction) that limit the possibilities of employers to react on price increases with saving on the respective labor. The pattern that matches most closely our expectations, $Elipi > Elcpc > Elapa$, appears in four out of twelve industries.

We now turn to the cross-price elasticities. These can have mixed signs and provide an indication of factor substitutability (positive sign) and factor complementarity (negative sign) between labor of different type. Cross-price elasticities are statistically different from zero in each industry and show remarkably similar patterns across industries. For instance, abstract and codifiable labor appear as substitutes everywhere. The magnitude of the effect of a one-percent increase in the price of abstract labor on the demand for codifiable labor (and vice versa, respectively) varies between .06 and .38 percent. Moreover, there is equally strong evidence suggesting that abstract and interactive labor complement each other with cross-price elasticities between -.09 and -1.3 percent. Our elasticity estimates for codifiable and interactive labor, except for two industries (plastics and rubber; iron and steel), point toward substitutability, with a between- industry variation in the range of that of abstract and codifiable labor.

which show highest reaction of codifiable tasks demand to own-price changes.

Table 3.1: Labor price elasticities by industry

(a)

Glass, ceramics, and bricks			Chemicals and pharma			Construction		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.472***	.220***	-.315***	-.270***	.162***	-.268***	-.331***	.251***	-.462***
(.01)	(.01)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.289***	.174***	.115***	-.393***	.219***	.174***	-.274***	.200***	0.074***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.545***	-.433***	.199***	-.557***	-.631***	.303***	-.371***	-.986***	.199***
(.02)	(.01)	(.02)	(.02)	(.02)	(.01)	(.02)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

(b)

Electrical equipment			Iron and steel manufacturing			Machine engineer./office mach.		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.345***	.206***	-.146***	-.481***	.240***	-.711***	-.300***	.241***	-.175***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.450***	.285***	.165***	-.097***	.136***	-.039***	-.500***	.297***	.203***
(.01)	(.01)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.604***	-.342***	.279***	-.285***	-1.173***	-.113***	-.568***	-.442***	.418***
(.03)	(.02)	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

(c)

Metal production			Precision engin, optics, watches			Plastics and rubber		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.361***	.088***	-.646***	-.305***	.119***	-.093***	-.546***	.376***	-.840***
(.01)	(.01)	(.01)	(.01)	(.00)	(.01)	(.01)	(.01)	(.02)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.142***	.064***	.078***	-.513***	.196***	.317***	-.009	.202***	-.192***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.01)	(.00)	(.01)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.645***	-1.094***	.182***	-.533***	-.132***	.271***	.294***	-1.313***	-.560***
(.02)	(.02)	(.02)	(.01)	(.01)	(.00)	(.01)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

(d)

Motor vehicles			Retail			Wholesale		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.452***	.240***	-.326***	-.307***	.078***	-.109***	-.169***	.173***	-.103***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.01)	(.00)	(.01)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.275***	.203***	.072***	-.418***	.139***	.279***	-.679***	.364***	.315***
(.01)	(.00)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.555***	-.608***	.159***	-.347***	-.099***	.140***	-.234***	-.165***	.241***
(.02)	(.02)	(.02)	(.01)	(.01)	(.00)	(.01)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

3.5.2 IT and non-IT capital elasticities

Table 3.2 presents the capital-labor elasticities and outsourcing-labor semi-elasticities calculated by using the coefficients from the system of demand and cost functions. We first draw our attention on a potential skill bias of capital. One prevalent pattern accross the twelve industries in our sample is that non-IT capital, when significant, correlates negatively with labor of any type, indicating substitutability. The range of non-IT elasticity estimates lies between -.03 and -.09, meaning that a one-percent increase in non-IT capital stock is associated with a drop in labor demand of .03 to .09 percent. Since our estimated elasticities show no considerable differences across task types, neither in magnitude nor in sign, we see no bias of non-IT capital toward labor of any particular type.

In the case of IT capital, our results are not consistent with economy-wide homogeneity of substitution patterns. IT capital is seldom significantly correlated with changes in the demand for task-differentiated labor - we find effects only in one third of the industries. IT substitutes for labor in some industries and complements it in others. In glass, bricks, and ceramics as well as in construction, plants that increase their IT capital stock decrease the employment of labor of *any* type. For example, a one-percent increase in IT capital in glass, bricks, and ceramics correlates with a .041 percent decrease in the demand for abstract labor, a .044 percent decrease in the demand for codifiable labor, and a .046 percent decrease in the demand for interactive labor. The magnitudes of the elasticities are apparently quite similar for the various labor types and indicate a rather low economic significance. The construction industry exhibits a comparable pattern. On the other hand, our results for chemicals and pharma as well as precision engineering, optics, and watches suggest complementarity between IT capital and labor, while again all types of labor are affected in the same way. Here again the elasticties' magnitudes are economically small; they range from .034 to .062. In fact, we do not observe a single industry where the relations between IT capital and labor behave according to the patterns suggested in Autor, Levy, and Murnane (2003) and Spitz-Oener (2006), among others.[29]

[29] In line with earlier empirical studies on the determinants of occupational composition of em-

First, with the current design we can only measure changes in the task quantities that stem from the acquisition or release of labor of certain type at the level of plants. In other words, our investigation is informative when it comes to the relations between technologies and demand for tasks that occur *due to changes in the occupational structure* at the establishment level. Therefore, we do not claim that our results provide evidence for absence of asymmetric effects of IT capital on the overall task demand. Such effects may still be present but result in *within-occupational* task up- or downgrading. Second, as argued in Aguirregabiria and Alonso-Borrego (2001), the decision to introduce technological capital for the first time has much more explanatory power for changes in the occupational composition of labor than the continuous decision of increasing the (already existing) stock of IT capital. Unfortunately, we have no infomation on the IT investment behavior of plants before our period of observation starts. Finally, due to the short panel, we are limited in the choice of lag structure between changes in capital stock and changes in labor demand. The timing between technological changes and shifts in labor demand may have complex dynamics which are difficult to capture with the current design.

ployment, we find that the elasticities with respect to non-IT capital tend to be larger than the elasticities with repect to IT capital. Moreover, elasticity estimates using data on individual firms or plants by Dunne, Haltiwanger, and Troske (1997) for the us, Aguirregabiria and Alonso-Borrego (2001) for Spain, and Addison et al. (2008) for Germany are with the same order of magnitude as the ones we obtain.

Table 3.2: Labor-technology and labor-outsourcing elasticities

(a)

Glass, ceramics, and bricks			Chemicals and pharma			Construction		
Abstract tasks								
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.041*	-.911	-.020	.035*	.118	-.050	-.032**	-.152	-.082***
(.03)	(.70)	(.03)	(.02)	(.31)	(.03)	(.02)	(.48)	(.02)
Explicit tasks								
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
-.044**	-.320	-.020	.034*	-1.313***	-.046	-.027*	-.052	-.090***
(.03)	(.55)	(.03)	(.02)	(.40)	(.03)	(.02)	(.18)	(.02)
Interactive tasks								
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
-.046**	2.661	.007	.045**	2.247*	-.059*	-.038**	-.273	-.070***
(.03)	(2.07)	(.03)	(.02)	(1.20)	(.03)	(.02)	(.97)	(.02)
R^2cost		.33			.31			.33
R^2demand abstract		.90			.92			.90
R^2demand codifiable		.94			.90			.91
Observations		349			382			1727

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

(b)

Electrical equipment			Iron and steel manuf			Machine engineering.		
Abstract tasks								
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.005	-3.824***	.036	-.022	-.177	-.046	.025*	-.096	.012
(.03)	(1.44)	(.03)	(.03)	(.12)	(.04)	(.01)	(.13)	(.02)
Explicit tasks								
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
-.010	-2.677**	.025	-.012	-.065	-.069*	.017	-.387	.011
(.03)	(1.08)	(.03)	(.03)	(.45)	(.04)	(.01)	(.25)	(.02)
Interactive tasks								
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
.006	14.316***	.035	-.012	-.501	-.044	.007	-.201	.015
(.03)	(4.88)	(.03)	(.03)	(1.23)	(.04)	(.01)	(.61)	(.02)
R^2cost		.14			.23			.32
R^2demand abstract		.29			.88			.21
R^2demand codifiable		.64			.97			.68
Observations		314			394			940

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

(c)

Metal production			Precision engin/optics/watches			Plastics and rubber		
Abstract tasks								
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.005	-.142	-.021	.042*	-1.214	-.075***	.0003	-.582	-.078***
(.02)	(.38)	(.02)	(.02)	(.35)	(.03)	(.03)	(.90)	(.03)
Explicit tasks								
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
-.005	-.427*	-.033*	.062***	-.581*	-.071***	-.006	.368	-.075***
(.02)	(.23)	(.02)	(.02)	(.33)	(.03)	(.03)	(.49)	(.03)
Interactive tasks								
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
.015	-.129	-.052***	.046**	.312	-.070**	.003	1.979**	-.052*
(.02)	(.76)	(.02)	(.02)	(1.03)	(.03)	(.03)	(.92)	(.03)
R^2cost		.31			.34			.38
R^2demand abstract		.92			.86			.71
R^2demand codifiable		.96			.84			.95
Observations		844			333			384

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

(d)

	Motor vehicles			Retail			Wholesale	
				Abstract tasks				
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.001	-.665**	-.012	.020	1.03	-.046***	.017	-.272**	-.076***
(.03)	(.32)	(.04)	(.02)	(1.11)	(.02)	(.02)	(.13)	(.02)
				Explicit tasks				
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
.010	-.453	-.024	.019	.849	-.043**	.013	.321	-.078***
(.03)	(.46)	(.04)	(.02)	(.70)	(.02)	(.02)	(.29)	(.02)
				Interactive tasks				
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
-.004	1.217	-.003	.022	-1.313	-.047***	.009	-.726**	-.077***
(.03)	(1.01)	(.04)	(.13)	(1.00)	(.02)	(.02)	(.32)	(.03)
	R^2cost	.40			.29			.37
	R^2demand abstract	.58			.98			.84
	R^2demand codifiable	.83			.97			.37
	Observations	377			812			657

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

3.5.3 Outsourcing semi-elasticities

Outsourcing appears to be the only factor that induces asymmetric changes in the demand for labor of different tasks. The outsourcing semi-elasticties indicate trends that fit the reasoning of Blinder (2006, 2009). We expect that the presence of outsourcing is associated with declines in both abstract and codifiable labor and that it is neutral or even favorable for interactive labor. According to our results, in one third of the industries (chemicals and pharma; electrical equipment; metal production; precision engineering) the presence of outsourcing is associated with declines in the codifiable labor demand. The magnitude of the effects varies between -.43 percent in metal production to -1.31 percent in chemicals and pharma. The presence of outsourcing is also associated with declines in the demand for abstract labor in three industries (electrical equipment; motor vehicles; wholesale), with semi-elasticities of -3.82, -.67, and -.27 percent, respectively. The results also suggest that in electrical equipment abstract labor is even more adversely affected by outsourcing than codifiable labor (the presence of outsourcing is associated with a 3.82 percent decrease in abstract labor and a 2.68 percent decrease in codifiable labor). Finally, the semi-elasticities for interactive labor are significant in four out of twelve industries (chemicals and pharma; electrical equipment; plastics and rubber; wholesale). In the first three industries mentioned before, the presence of outsourcing is associated with increases in the demand for interactive labor (2.25, 14.32, and 2 percent, respectively). Only wholesale displays an unexpected pattern: here the presence of outsourcing is negatively associated with the demand for interactive labor ($EliOUT$=-.73).

Since we see much inter- industry variation in the outsourcing-labor relations, the natural question arises why this is so. As argued before, we see two possible sources of variation. First, if industries employ qualitatively different production processes, the type of production being outsourced may differ significantly. In the light of our empirical findings, chemicals and pharma, electrical equipment, metal production, as well as precision engineering may be in process of outsourcing assembly-type of production and therefore downsize labor that makes intense use of codifiable tasks. Wholesale, on the other hand, may be outsourcing some non-core service processes that involve labor that makes use of intellectual and interactive tasks. Second, industries may exhibit qualitatively similar outsourcing patterns, but some of them might have taken the lead in outsourcing earlier than others. In this line of reasoning and given our empirical results, vehicle production likely outsourced most of their assembly line processes during the 1990s (Geishecker 2002) and turned to outsourcing units with more complex tasks in the period we observe. Other manufacturing industries with production processes similar to those in motor vehicles may have started outsourcing later and are thus still primarily outsourcing assembly line-types of processes (e.g., chemicals and pharma; electrical equipment; metal production; precision engineering).

3.6 Sensitivity analysis

We have specified alternatives to the main model in order to check for the robustness of the results. As elaborated in section 3.2, we use two indicators of knowledge codification. In the above-presented results we use the expliciteness of tasks as an indicator of codification. Hence, we estimated the same system of cost and demand functions as before, but now instead of explicit tasks quantities as a measure of codifiable labor, we include repetitive tasks quantities. The results (available from the authors on request) for this second set of regressions are remarkably similar to the results of the estimation including explicit tasks for all elasticities except for the semi-elasticities with respect to outsourcing in precision engineering, optics, and watches.

Our data do not permit us to see how qualitatively different the reported IT investments are across industries. It is an assumption that the quality of capital across industries varies. At the same time, due to the fact that our task measures are occupation-specific, we assume that an occupation has the same task composition across industries. One concern that arises is whether the differences we see across industries stem from the differences in the technologies they employ, or from the differences in the task composition used by seemingly identical occupations in different industries. For example, one can rightfully ask whether the task portfolio of a manager in chemicals is significantly different from the one of a manager in retail? If the managers in chemicals have on average significantly higher intensity of abstract content than those in retail, it may be advisable to account for these differences in the analysis. After the inspection of the industry-occupation relations in our data we noticed two favourable properties of the current design. First, our industries are broadly specified such that many of the occupations become unique to certain industries. Second, the results of the analysis of variance, where the variance of each tasks we use is regressed on the occupational and industry dummies, shows that most of the task variation is explained by the occupational and to lesser extent by the industry dimension. The main results of the ANOVA are presented in Table 3.3. For example, for R&D tasks, although the industry dummies explain a significant share of the variance of the R&D tasks' intensity, the mean sum of squares of the occupational categories is almost three times larger than the one of the industry dummies (.88 vs. .30). The total sum of squares explained by the occupational dummies is almost 48 times larger than the sum of squares explained by the industry dummies (127.87 vs. 2.68).

Table 3.3: Occupational vs. the industrial task variation

Source	Patial SS	df	MS	F	p	Partial SS	df	MS	F	p
Coordinate, organize						*Sales, PR*				
Model	116.23	154	.75	9.24	.00	1.32	154	.07	4.85	.00
Occupation	111.25	145	.77	9.39	.00	9.24	145	.06	4.61	.00
Industry	2.05	9	.23	2.79	.00	.17	9	.02	1.39	.19
$Adj R^2$	.73					.56				
R&D						*Management*				
Model	136.52	154	.89	13.96	.00	12.84	154	.08	5.67	.00
Occupation	127.87	145	.88	13.89	.00	12.37	145	.09	5.8	.00
Industry	2.68	9	.3	4.69	.00	.13	9	.01	.95	.48
$Adj R^2$	.81					.61				
Negotiate						*Medical knowledge*				
Model	113.57	154	.74	13.36	.00	4.78	154	.03	3.4	.00
Occupation	107.05	145	.74	13.37	.00	3.73	145	.03	2.82	.00
Industry	.61	9	.07	1.23	.27	.37	9	.04	4.57	.00
$Adj R^2$	.8					.44				

Taking care of people						*Explicit knowledge*				
Model	64.1	154	.42	4.52	.00	206	154	1.34	3.78	.00
Occupation	39.5	145	.27	2.96	.00	188.06	145	1.3	3.67	.00
Industry	3.92	9	.44	4.73	.00	3.94	9	.44	1.24	.27
$Adj\,R^2$	.53					.47				
Mathemantics, statistics						*Repetitive knowledge*				
Model	16.36	154	.11	2.23	.00	202.25	154	1.31	5.15	.00
Occupation	15.64	145	.11	2.26	.00	194.42	145	1.34	5.26	.00
Industry	.4	9	.04	.93	.50	2.09	9	.23	.91	.51
$Adj\,R^2$	.29					.57				
Foreign languages										
Model	1.41	154	.07	2.82	.00					
Occupation	9.02	145	.06	2.59	.00					
Industry	.83	9	.09	3.84	.00					
$Adj\,R^2$	.37									

Source: QCS 1998/99, ANOVA estimations. Note: There are 9 instead of 12 industries because the industrial classification in the survey is different from the one in the LIAB.

However, there is still a significant share of variation in many tasks that is explained by the industry dummies after controling for the occupational dimension. Therefore, it would be advisable in next versions to replace the occupational classification with a classification that further distinguishes the occupations by industries as well.

3.7 Conclusions

The recent scientific discourse on the impact of technology and outsourcing on the labor market suggests the idea that the demand for different skills is not uniformly affected by technological and organizational change. Following authors such as Autor, Levy, and Murnane (2003), Spitz-Oener (2006), Goos and Manning (2007), as well as Blinder (2009), one can hypothesize that repetitive or routine tasks should be easily substitutable by technology and at the same time internationally outsourceable. Moreover, labor of any kind that does not involve direct contact with customers should possess certain proneness to be outsourced to another sector, region, or country. This also holds for labor that mainly performs problem-solving tasks. Nevertheless, problem-solving and complex thinking skills (i.e., abstract tasks) should be complementary to technology. It is furthermore argued that tasks involving customer-interaction (i.e., interactive tasks) can neither be outsourced nor substituted by technology. Previous research on the empirical plausibility of these hypotheses has largely focused on economy-wide patterns. It has often been mute on potential inter- industry differences in the nature of the technology-outsourcing-labor nexus. Variation among industries in the capital-labor (outsourcing-labor) relations stem from differences in the types of production processes employed (outsourced). In the case of outsourcing, they also stem from the cross-sectoral differences in the outsourcing stage. The main purpose of this article is to test for inter-industry idiosyncrasies in the capital-labor and outsourcing-labor relations.

Using a sample of twelve German industries in the period 2001-2005, we explore the relations between the demand for heterogeneous labor on the one hand and capital and outsourcing on the other hand. Our results are only to a certain degree consistent with the predictions outlined above. First, perhaps most at odds with previous studies are our results for technology as captured by IT capital. In the industries where we observe significant effects, IT elasticities are either positive for all types of labor (chemicals and pharma; precision engineering, optics, and watches) or negative througout (glass, bricks, ceramics; construction). Moreover, the magnitude of the elasticities of demand for task-differentiated labor with respect to IT capital is fairly small. Nevertheless, we do not claim that our results provide evidence for the absence of effects of technology on labor demand. Such effects may still be present but result mainly in within occupational task up- or downgrading, something we cannot observe with the current empirical design. This is one evident shortcoming of the current approach.

Second, our results provide some evidence against the capital–skill complementarity conjecture advanced originally by Griliches (1969). One of the most salient patterns across the twelve industries in our sample is that non-IT capital is associated with declines in the employment of labor of any type, indicating a substitutive relationship. The magnitude of the substitution effects is economically small, although higher than that of IT capital.

Third, our findings for outsourcing closely match the predictions posited by Blinder (2009). In half of the industries we find an indication of an adverse effect of outsourcing either on codifiable or on abstract labor, or on both. At the same time, outsourcing is either neutral or favorable to the demand for interactive labor in all but one industry.

Fourth, when it comes to the substitution patterns between labor of different types, we capture the following: abstract and codifiable labor appear as substitutes in all industries, abstract and interactive labor appear as complements everywhere, while interactive and codifiable labor show a substitutive relationship in ten industries and complementarity in two.

We conclude that in our exploration of skill bias in the capital-labor and outsourcing-labor relationships among industries the only notable variation we see is in outsourcing. The results support the reasoning about international outsourcing put forward by Blinder (2006, 2009).

Chapter 4

Human capital mismatches along the career path

Recent research finds that human capital is more general than previously thought and that staying within occupations with high task/skill overlap is a significant source of individual wage growth. What has not gained enough insight so far is that there are non-negligible asymmetries in the transferability of human capital when comparing a job move from occupation i to j to a job move from j to i. This article contributes to the measurement of such asymmetries and to an understanding of their consequences on people's occupational switching patterns and earnings' differences.

Both, Poletaev and Robinson (2008) and Gathmann and Schönberg (2010) offer measures of distance between occupations based on the information about the overlap in the skills/tasks across occupations. Geel and Backes-Gelner (2009) make a similar attempt. The common idea incorporated in these articles is to measure distance between occupations as the degree of the skill/task mismatch between pairs of occupations. Gathmann and Schönberg (2010) use angular separation to measure occupational distance in a 19-dimensional task space. Poletaev and Robinson (2008) first use factor analysis to reduce the number of tasks into four basic skills and then develop categorical measures of occupational distance which they refer to as 'skill portfolios'.

In this article we claim that the concept of 'occupational distance' fails to appreciate the inherent human capital asymmetry in occupational pairs. The asymmetry of human capital between occupations requiring similar types of skills stems from the differences in their skill complexity. An electrical engineer may use similar skills as an electrical engineering technician, however, the first job will involve tasks that are more complex and require a higher level of these skills than the latter one. Furthermore, people can move parallel and upward the occupational complexity ladder, but downward movements are also common. The asymmetry remains hidden when using the symmetric occupational distances between occupations that have been developed so far. We therefore develop a measure of occupational distance that is asymmetric. In particular, we typify a combination of occupations by two different measures: human capital redundancy and human capital shortage. Human capital redundancy measures the amount of human capital associated with the first job that becomes idle in the second job. Human capital shortage quantifies how much human capital an employee requires in the second job that had not yet been acquired in the first job.

We find that the human capital mismatch has implications for the mobility decisions and the wage offer at the new occupation. Individuals change occupations in a manner that reduces the amount of human capital that would remain idle at the new job. Moreover, they also move to occupations where the amount of new skills they need to acquire is small. Exceptions are employees with few years of labor market experience who change occupations voluntarily. Such employees do not minimize the amount of skills that need to be learnt when changing occupations. We propose that this reflects movements upward the career ladder aimed at long-term maximization of earnings. We further find that employers penalize new employees for having a shortage of skills by giving them lower wage offers and reward employees for having redundant human capital through somewhat higher wage offers. These results also hold after sample selection and endogeneity corrections. Interestingly, the analysis of the wage growth at the new job (occupation) reveals that the initial wage offer penalty gets compensated through higher wage growth for employees with initial skill shortage. We speculate that this reflects productivity increases resulting from on-the-job learning. The finding is in line with our expectation that job-hopping is used by young employees to acquire new skills and increase lifetime earnings.

The article further develops a measure of skill experience that captures the individual accumulation of skills along a labor market experience path. Similar to Gathmann and Schönberg (2010) we show that skill experience is an important component of a person's human capital, more so than firm- and occupation-specific human capital. We additionally propose a distinction between skill experience that is useful in the current job and skill experience that is useless. Useful skill experience indeed has a vastly stronger positive effect on wages than the seemingly useless one. However, also useless skill experience raises wages, though only moderately, indicating that skills that do not match the typical skill profile of an occupation may still have some value.

In the remainder of this study, we will first explain the construction of human capital mismatch measures (section 4.1) and we will introduce our data and basic descriptives in section 4.2. Then we will test the predictive power of the measures of human capital asymmetries on the frequency of moves between occupations in section 4.3 and on the wage dynamics in section 4.4. Section 4.5 introduces the definitions of useful and useless skill experience and tests them empirically. Section 4.6 concludes.

4.1 Human capital redundancy and human capital shortage

In what follows we will assume that each occupation has a specific skill-profile. A skill-profile expresses the intensity with which each of k different broad skill categories that exist in the economy are required to fulfill the tasks associated with a job in the occupation. As an example, one may think of such categories as cognitive skills, manual dexterity, or social interaction skills. As a consequence, an occupation's skill-profile can be depicted as a k-dimensional skill-vector. In Figure 4.1, we show an example of two different occupations, with k equal to 2.

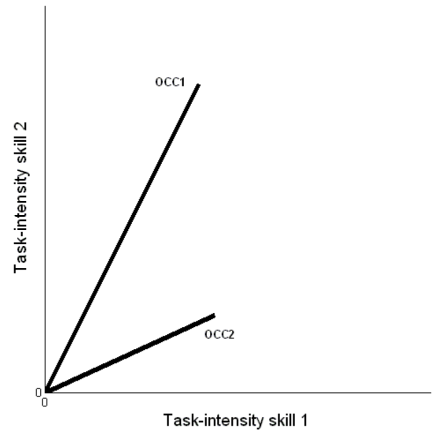


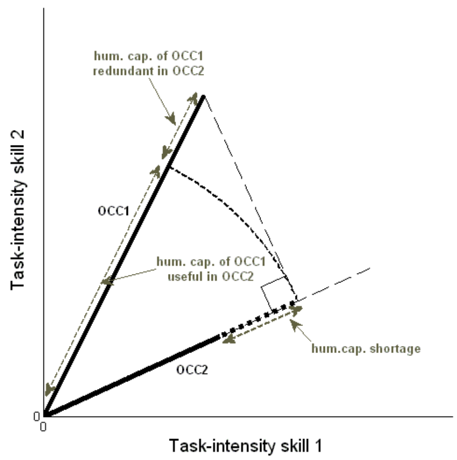
Figure 4.1: Skill-profiles of two occupations in two-dimensional skill-space

In principle, the angle between the two vectors indicates whether occupations have similar task structures. For instance, Gathmann and Schönberg (2010) use the angular separation between skill-vectors as a measure of occupational distance.[1] However, some occupations require more complex skills than other occupations. As such, the relative importance of a task (and its corresponding skill) does not give much information about the human capital similarity between two occupations. For instance, the relative importance of social interaction skills may be similar for an ordinary sales person and for a professional negotiator. However, the absolute intensity of this task factor is likely to be far greater for the latter than for the former. The reason is that although the negotiator can be thought of as an advanced sales person, his job is vastly more complex. In the example of Figure 4.2, for OCC1, people require a relatively high amount of skill 2, whereas OCC2 relies more heavily on skill 1. However, the length of OCC1's skill-vector is greater than of OCC2's skill vector. In fact, although OCC1 requires relatively less of skill 1 than does OCC2, the absolute skill

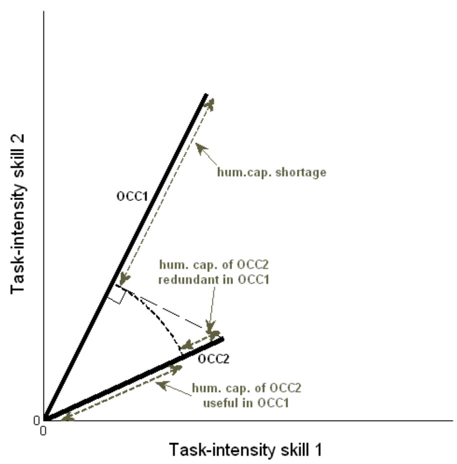
[1] In the empirical section, we will deviate to some degree from their design in the way we use the information from the German survey that investigates whch tasks employees use in their job.

requirements for skill 1 are about the same in both jobs. The reason for this is that OCC1 is more complex than OCC2. In other words, OCC1 does not only involve a different skill-mix, but also a different skill-intensity. The complexity of a job is likely to be reflected in the length of the education that is necessary to carry out the job. In the section 4.2 we will, therefore, use the average educational attainment of employees in an occupation to define the length of the skill-vector.

This difference in skill-intensity between jobs introduces asymmetries in the job switches between two occupations. Figure 4.2 show the human capital implications for the case that a person moves from OCC1 to OCC2 and vice versa.



(a) Move from OCC1 to OCC2



(b) Move from OCC2 to OCC1

Figure 4.2: Move from OCC1 to OCC2 and vice versa

We are interested in how much of the skills an employee required for his old job remains useful in his new job. To this end, we decompose the old occupation's skill-vector into a component parallel to the new occupation's skill-vector and one perpendicular to it. In Figure 4.2 we accordingly projected the skill-vector of the previous occupation of the job switcher onto the skill-vector of his new occupation. This projection shows how much of the skills required in the old occupation are also useful in the new occupation. If we subtract the length of this projection from the length of the old occupation's skill-vector, we get the amount of the job switcher's human capital that remains idle in the new occupation. This is shown by rotating the projection back onto the old occupation's skill-vector. We call this idle human capital the human capital redundancy that is involved in a job switch. When comparing Figure 4.2(a) to Figure 4.2(b), it is interesting to note that, although OCC2 is less complex than OCC1, in both, a job move from OCC1 to OCC2 and from OCC2 to OCC1, human capital redundancies arise.

If instead of comparing the projection to the old occupation's skill-vector, we compare it to the new occupation's skill vector, we get an indication of how well equipped the job switcher is for his new job. In the graphs, we subtract the length of the projection from the new occupation's skill-vector. The result is the human capital shortage the job switcher incurs. In Figure 4.2(b), the job switcher from OCC2 to OCC1 faces large human capital shortages as OCC1's skill-vector is far longer than the projection of OCC2's skill-vector. However, in Figure 4.2(a), depicting a move from OCC1 to OCC2, the projection of the relatively complex skill-vector of OCC1 exceeds the length of the skill-vector of OCC2. In this situation, there is in fact a negative human capital shortage, or a human capital surplus.

Let L_1 and L_2 be the length of OCC1's and OCC2's skill-vectors. The length of the projection of OCC1's skill-vector onto OCC2's skill-vector (i.e., the line segment indicated by 'hum.cap. of OCC1 useful in OCC2'), $P_{1,2}$, can be calculated as follows:[2]

$$P_{1,2} = \frac{\vec{\nu_1} \cdot \vec{\nu_2}}{L_1 L_2} L_1 \tag{4.1}$$

Where $\vec{\nu_1}$ and $\vec{\nu_2}$are the skill-vectors of OCC1 and OCC2 and is used for the dot-product. Human capital redundancies involved in a move from OCC1 to OCC2 are now defined as:

[2]The first term of the right hand side expression is the angular separation, i.e., the arccosine of the angle between $\vec{\nu_1}$ and $\vec{\nu_2}$. Equation (1) now follows from using simple trigonometry and canceling out the functions cos(arccos).

$$Redun_{1,2} = L_1 - P_{1,2} \tag{4.2}$$

Human capital shortage involved in the move depicted in Figure 4.2(a) is the relative human capital deficit that the job switcher faces in his new job. We can calculate this as follows:

$$Short_{1,2} = L_2 - P_{1,2} \tag{4.3}$$

To summarize, we use the skill profiles of occupations to express a job switch in an occupational pair by two different variables. The first variable, human capital redundancy, measures how much of the human capital associated with the old job is rendered idle by moving to the new job. The second variable, human capital shortage, measures how much of the human capital required in the new job still needs to be acquired given the human capital requirements in the old job. This results in an asymmetric description of the job switches in an occupational pair. The set of measures is considerably richer than corresponding symmetric distances like the angle between the skill-vectors of OCC1 and OCC2 or the Euclidian distance between the tips of the task vectors of OCC1 and OCC2, which takes into account the complexity of occupations, but does not yield asymmetric measures.

4.2 Data and descriptive statistics

We use two datasets for our analysis: the QCS and the IAB Employment Samples (IABS). The first dataset is our source of occupational task and knowledge information and is used for construction of the occupational skill profiles and the measures of human capital mismatch, while the second dataset contains the individual level employment histories including occupational mobility and wages. The information from the first dataset is merged with the IABS at the occupational level.

4.2.1 Qualification and Career Survey

The QCS was already explained in section 2.3 of chapter 1. We use the 2005/2006 survey for the purpose of this study because this is the survey with most detailed educational information which we use to assess the level of complexity of an occupation's set of tasks. We focus on the answers to 52 questions that shed light on the task and knowledge structure of the respondent's job and on his or her education. As we are interested in the skill structure associated with particular occupations, we calculate averages of the scores on the questions and of the individual's schooling for each occupation. After dropping all observations from Eastern Germany and all occupations with fewer than 10 respondents we obtain a sample of 16,037 respondents in 118 different occupations.

Factor analysis

Although we selected 52 questions we are likely to identify a smaller number of broad tasks (or skills needed to carry out these tasks). Some of the tasks referred to in the 52 questions might be rather similar in the skills they require and it should be possible to carry them out with the same human capital. In fact, the average absolute cross-correlation between the answers to the 52 questions is 37%. Therefore, we chose to deviate from the approach used by Gathmann and Schönberg who treat each question as corresponding to a separate task. Instead we use factor analysis to extract 6 factors that account for 85% of total variation. The resulting factors could be labeled (1) cognitive, (2) manual, (3) engineering, (4) interactive, (5) commercial and (6) security. Table C7 in appendix C contains the factor loadings on each of the 52 questions listed in Table C1.

For each occupation, we now have factor loadings representing the intensity with which a task is used in an occupation. Factor loadings can be both positive and negative, but it is hard to interpret what it means that an occupation uses a specific skill with a negative intensity. Therefore, following Poletaev and Robinson (2008), for each factor, we rank factor scores of different occupations. This provides us with vectors whose elements contain percentile positions of an occupation on a skill-factor that range from 0 to 1. As we believe that employees are likely to report task intensities relative to the intensity with which they use other tasks and not relative to how intense the task is used in other occupations, we normalize all these vectors to have unit length. As a last step, we add information on the complexity of an occupation's task profile by multiplying the vectors with the number of years of schooling employees in the occupation took on average[3]. As a result, the units in which human capital shortages and redundancies that characterize an occupation switch are measured reflect the number of years of schooling that are lacking or remain idle.

To illustrate this, consider an electrical engineer ('Elektroingenieur') that becomes a mechanic ('Maschinenbautechniker'). This person would render .48 years of his human capital redundant and have 2.97 years of human capital surplus in his new job. The reason is that, although the electrical engineer uses quite similar skills as compared to the mechanic (the angle between the task vectors is only 15.1°) his education is typically 3.45 years longer. The reverse move, from mechanic to electrical engineer, would involve about the same human capital redundancies: .36 years of the mechanic's human capital is rendered idle. However, the mechanic would face major problems in acquiring the skills needed for his new job: the human capital shortage for this move is 3.81 years of schooling.

The asymmetries that arise when comparing a move from an occupation i to an occupation j with the reverse move conform to the intuition we have about such moves. For instance, university professors experience more human capital redundancies when they become high school professors than vice versa, and the same holds for medical doctors that become nurses. However, this information is lost in currently available distance measures. For instance, regardless of the direction of the move,

[3]We have information on the exact number of months an individual spent on tertiary and university education. To that, we add the number of years that correspond to the highest level of secondary education the individual acquired, excluding primary school. That is, Hauptschule and Realschule are both counted as yielding 5 years of education and Abitur represents 9 years of education.

the Euclidian distance between an electrical engineer and a mechanic is 4.69 years of education and the angular distance is about 15.1°. In the next section, we show that these asymmetries indeed add to our understanding of cross-occupational labor mobility and the wage dynamics involved.

Table 4.1 lists the occupational movements with (a) highest and (b) lowest human capital redundancies, and with (c) highest, and (d) lowest human capital shortages. The human capital variables are expressed in years of education. Of all possible occupation switches in the economy, a mechanical engineer that becomes a household cleaner would incur the highest human capital redundancy. Skills representing over 13 years of education would become idle. The movement with lowest human capital redundancy is from a sheet metal presser to a generator machinist. The largest shortage in skills in an occupation switch occurs if a household cleaner becomes a mechanical engineer, while the largest surplus occurs if a physician would become a sheet metal presser.

Table 4.1: Highest and lowest possible human capital redundancies and shortages

a. Occupational switches with highest human capital redundancy		HC redundancy
Mechanical, motor engineers	Household cleaners	13.28
Electrical engineers	Household cleaners	11.65
Mechanical, motor engineers	Postal deliverers	11.54
Architects, civil engineers	Household cleaners	11.52
Mechanical, motor engineers	Motor vehicle drivers	11.34
b. Occupational switches with lowest human capital redundancy		**HC redundancy**
Sheet metal pressers/drawers	Generator machinists	.01
Ceramics workers	Metal polishers	.01
Generator machinists	Sheet metal pressers/drawers	.01
Metal polishers	Ceramics workers	.01
Ceramics workers	Paper, cellulose makers	.02
c. Occupational switches with highest human capital shortage		**HC shortage**
Household cleaners	Mechanical, motor engineers	14.06
Postal deliverers	Mechanical, motor engineers	13.13
Household cleaners	Architects, civil engineers	12.98
Motor vehicle drivers	Mechanical, motor engineers	12.98
Glass, buildings cleaners	Mechanical, motor engineers	12.91
d. Occupational switches with lowest human capital shortage		**HC shortage**
Physicians	Sheet metal pressers/drawers	-8.68
Physicians	Iron, metal producers, melters	-7.9
Physicians	Ceramics workers	-7.07
Physicians	Moulders, coremakers	-7.01
Physicians	Metal workers	-7.01

4.2.2 IAB Employment Samples

The IAB Employment Samples (IABS), also explained in section 2.3 in chapter 1, stems from administrative data and enables us to follow complete work histories of employees over a period of up to 30 years. This includes information on occupational, industrial and regional attachment, daily earnings, several demographic characteristics, unemployment incidence and duration, and job changes. Since individuals can be followed over time, the sample is a panel. The data does not contain information on employees who are not subject to social security. This affects civil servants and self-employed. However, for the rest of the employees it is the largest and probably the most reliable source of employment information in Germany. Furthermore, the social security wage data is the most accurate information on wages in Germany because non-reporting or false-reporting is punishable by law. However, wages are right-censored and this affects yearly between 9% and 16% of all observations. When appropriate (e.g., sample of occupational pairs) we impute the wages using the method offered by Gartner (2005). The IABS and the QCS are matched at the occupational level. Although the QCS contains more detailed occupational categories, the IABS offers an occupational classification that is between the 2- and the 3-digit level. The matching results in 110 occupations.

4.2.3 Final samples

We restrict our analysis to all male employees in West Germany for the period 1976-2004. Furthermore, we drop all the observations that entered the sample in 1975 to avoid problems with incomplete (i.e. left censored) work histories, which would prohibit the construction of reliable experience measures. We also drop individuals that enter the labor market for the first time at an age of 35 or older. Turning to job switches, we distinguish between a sample of direct (job-job) mobile and indirect (job-unemployment-job) job switches[4]. While the direct job switches may be both, voluntary (quits) and involuntary (layoffs), the indirect job switches are a sample of layoffs. To guarantee that we select a sample of layoffs, we exclude from the indirect job switchers all individuals whose unemployment spell starts later than 84

[4]Previous studies (e.g. Gathmann and Schönberg 2010) use plant closures identified through the last record of an establishment in the administrative data. Hethey and Schmieder (2010) show that the administrative establishment ID changes in the IABS are severely misleading. "Only about 35 to 40 percent of new and disappearing EIDs with more than 3 employees correspond unambiguously to real establishmnt entries and exits".

days after the last employment because this is typical for quits.[5] From the samples we also exclude moves that follow a non-participation period of more than 2 years. Periods shorter than that are common because individuals often interrupt their labor market participation to obtain additional schooling. Each move that we consider is a move that includes occupational change.

Individual-level samples

The sample of direct occupational switchers has 132,795[6] observations involving 74,194 individuals over a period of maximum 29 years. 31.7% of these individuals have directly changed their occupation only once, while the rest 68.3% have two or more occupational changes. The sample of indirect movements contains 58,961 observations involving 38,949 individuals over a period of maximum 28.7 years. Here 45.1% have one indirect occupational change record, while the rest 54.9% have two or more. The distributions of the relevant variables in the direct and the indirect sample vary significantly. Table 4.2 show some descriptive statistics on the variables of interest in both samples.

[5]By law a person who quits a job is not eligible for unemployment benefits within the first three months after the quit. Therefore, those whose unemployment spell starts shortly after the last employment must be layoffs.

[6]The number of observations decreases when estimating the wage growth at the new occupation because fewer persons can be follwed over longer time periods.

Table 4.2: Descriptive statistics of occupational moves

(a) Direct moves

Variable	Mean	S.D.	Min.	Max.	Obs.
Deviation from occ. entrants' wage mean	.51	.44	-1.75	2.12	132,795
HC shortage	1.15	1.87	-6.59	11.51	132,795
HC redundancy	1.49	1.52	-.31	15.01	132,795
Experience	5.87	4.65	1.00	29.02	132,795
Age	29.50	6.30	18	62	132,795
Education	2.23	1.23	1	6	132,795
Wage growth after 1 year on the job	.04	.11	-1.51	1.61	69,911
Wage growth after 3 years on the job	.04	.05	-.43	.62	35,678
Wage growth after 5 years on the job	.03	.04	-.24	.37	21,062

(b) Layoffs

Variable	Mean	S.D.	Min	Max.	Obs.
Deviation from occ. entrants' wage mean	.37	.40	-1.69	2.00	58,961
HC shortage	1.14	1.81	-6.59	11.64	58,961
HC redundancy	1.62	1.51	-.31	17.32	58,961
Experience	4.94	4.10	1.00	28.69	58,961
Age	29.78	6.62	19	60	58,961
Education	2.04	1.09	1	6	58,961
Unemployment duration (in years)	.88	1.23	.00	21.53	58,961
Wage growth after 1 year on the job	.04	.11	-1.32	1.34	32,431
Wage growth after 3 years on the job	.04	.05	-.44	.48	14,713
Wage growth after 5 years on the job	.04	.04	-.30	.31	8,842

Note that wages are converted and deflated in 1995 DM and present the daily earnings. All experience variables (general, occupational, plant, and skill experience) are expressed in years. Unemployment length is also expressed in years. Education takes the following values: (1) no formal education, (2) high-school without A-levels (Abitur), (3) A-levels without vocational training. (4) A-levels with occupational training, (5) technical college, and (6) university. Occupational distance is measured as in Gathmann and Schönberg: one minus the angular separation, where we take the angular separation between the skill-vectors from our factor analysis.

Involuntary mobile receive significantly lower wage offers relative to their previous wage than direct occupational switchers. In fact, except for the group of occupational switchers who change jobs very early in their career, on average, involuntary mobile move to occupations where they undergo wage losses. The picture is different for the sample of direct moves. Here, occupational switching usually results in wage increases. Figure 4.3 graphs the average wage growth calculated as the difference between the immediate wage at the new occupation and the last wage earned before the switch (instantaneous wage growth) for different experience categories. This is presented for both, for the sample of direct and the sample of indirect occupational moves.

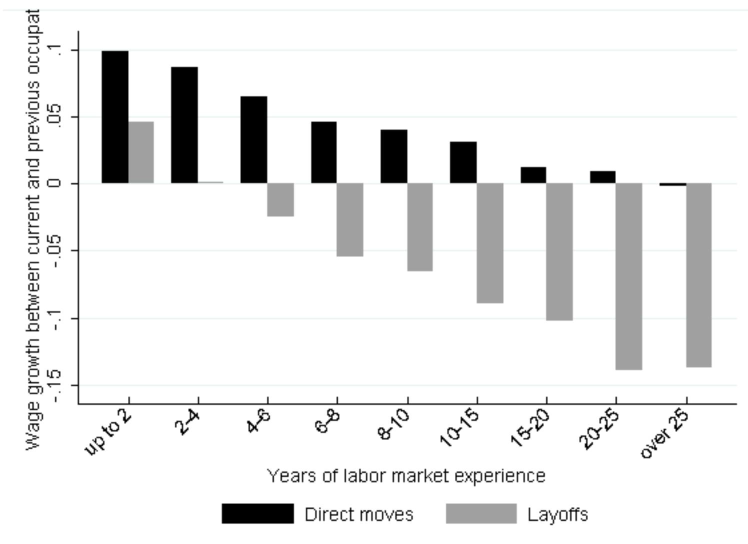
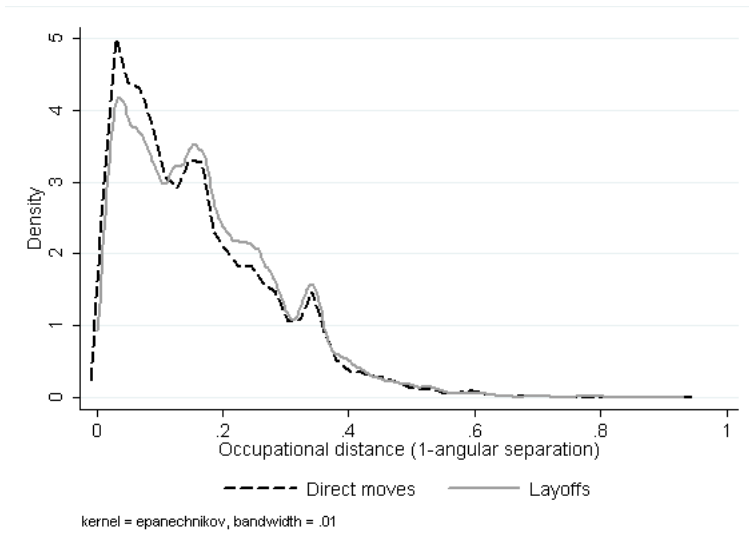


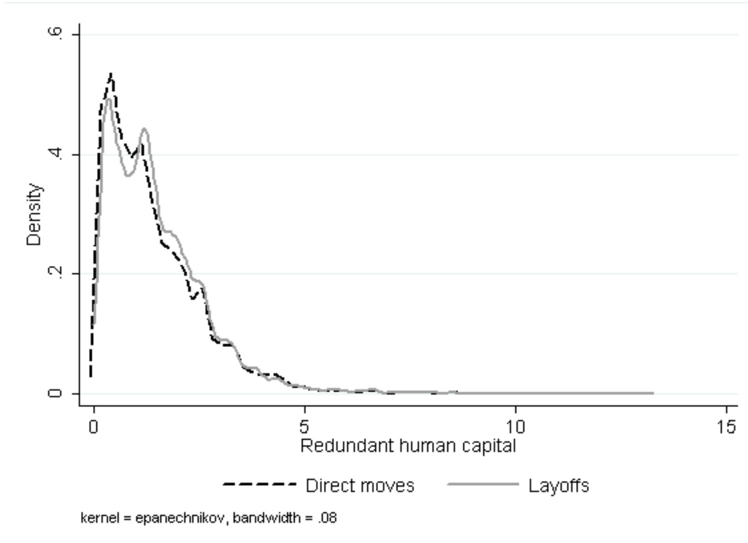
Figure 4.3: Wage growth of occupational switchers by experience

It is evident from Figure 4.3 that our two samples are inherently different. For example, indirect occupational switchers who change occupation in a period of 6 to 8 years of labor market experience on average undergo real wage losses of around 5.5%, while direct occupational switchers in the same experience category undergo an average real wage growth of around 4.6%.

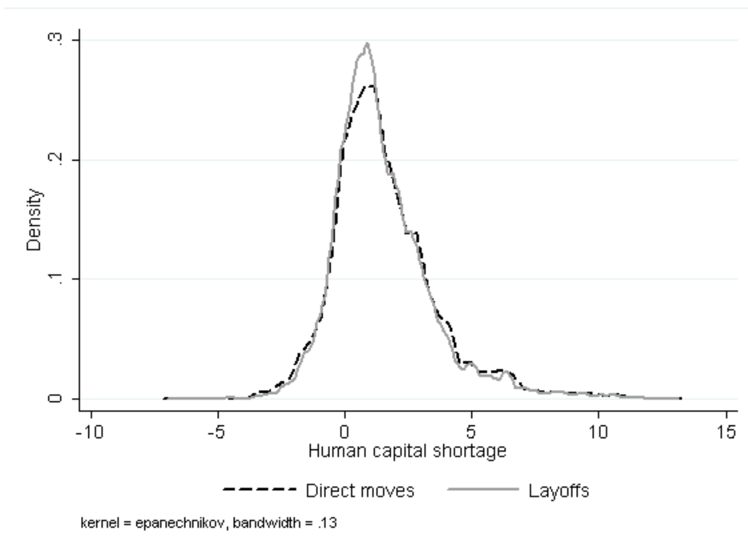
The discrepancies in the two samples are also evident in the human capital mismatch variables. Both, a t-test and a median test confirm that indirect moves have (1) significantly higher occupational distance, (2) significantly higher redundancy of human capital and (3) significantly lower human capital shortage when compared to the sample of direct moves. Figure 4.4 plots the densities of occupational distance, human capital redundancy and human capital shortage distributions for the two samples.



(a) Layoffs move to less similar occupations than direct switchers



(b) Layoffs incur higher human capital redundancy than direct switchers



(c) Layoffs incur lower human capital shortage than direct switchers

Figure 4.4: Occupational distance, HC redundancy and HC shortage densities by type of move

Occupational pairs samples

We create a sample at the level of the occupational pair. That is, the sample consists of all possible combinations of two occupations, excluding same-occupation combinations ($118^2 - 118 = 13,806$). We use this sample for the occupational switching estimations. The dependent variable is the count of moves (direct or indirect) between occupations, distinguishing movements from OCC1 to OCC2 from those from OCC2 to OCC1.

Table 4.3: Descriptive statistics of moves between occupational pairs

Variable	Mean	Median	Std. Dev.	Min	Max	Obs
Direct moves (up to 5 yrs. of exp.)	10.48	2	34.68	.00	1163	13,806
Direct moves (over 5 yrs. of exp.)	5.89	1	23.03	.00	848	13,806
Indirect moves (up to 5 yrs. of exp.)	5.9	1	17.9	.00	444	13,806
Indirect moves (over 5 yrs. of exp.)	2.03	0	6.74	.00	173	13,806
HC shortage	2.28	1.85	2.92	-8.68	14.06	13,806
HC redundancy	2.28	1.99	1.51	.01	13.28	13,806
Occupational distance	.24	.022	.14	.00	.94	13,806
Log employment in OCC1	18.51	18.73	2.04	11.81	23.78	13,806
Log employment in OCC2	18.51	18.73	2.04	11.81	23.78	13,806

4.3 Movements upward and downward the occupational complexity

In this section we analyse the relationships between occupational switching and our measures of human capital mismatch. We are interested in answering three questions: first, do our measures have explanatory power beyond a mere measure of occupational distance; second, do the patterns we see in these relationships differ between our two samples; and third, do the observed patterns differ by labor market experience groups? To tackle the first question we conduct an analysis of variance (ANOVA) where the movement counts between occupational pairs are regressed on the three measures of interest. From the partial sum of squares and the F statistics of Table 4.4

we see that the most powerful variable among human capital shortage, redundancy and occupational distance is human capital redundancy. Therefore, we can conclude that our measures do not only explain additional variance in the movements, but also appear superior to occupational distance in explaining occupational changes.

Table 4.4: Analysis of variance (ANOVA)

	Direct moves			Layoffs		
Source	Partial SS	df	F	Partial SS	df	F
Model	140.2	3	638.45	134.61	3	609.62
HC shortage	.64	1	8.73	2.76	1	37.49
HC redundancy	12.85	1	175.53	26.86	1	364.93
Occupational distance	.34	1	4.68	1.85	1	25.14
Residual	1010.3	13802		1015.89	13,802	
Total	1150.5	13805		1150.5	13,805	
R^2	.12			.12		
Observations	13,806			13,806		

Dependent variable: rank of the count of moves between occupational pairs. The independent variables are continuous and normalized with mean 0 and SD=1 for comparability.

To answer the second and the third question, we estimate negative binomial models[7] which predict the movement count between occupational pairs. We distinguish between two labor market experience categories: those with up to 5 years of general experience and those with over 5 years of general experience. Table 4.5 presents the results for both experience groups and for both, direct moves and layoffs.

In all models but in Model Ia people tend to move to occupations where they incur relatively small shortages of human capital. Human capital shortage does not seem to affect moves of less experienced people in the direct moves sample, while one standard deviation higher human capital shortage between occupations corresponds to a 10.5% decrease in the between-occupational direct moves for people with over 5 years of general experience. Hence, while people in general avoid moving to occupations where they incur human capital shortage, this is not so for the young employees who

[7] Our dependent variables are right-skewed and over-dispersed.

Table 4.5: Explaining mobility between occupational pairs

	Direct moves		Layoffs	
	Model Ia	Model IIa	Model Ib	Model IIb
Dependent variable →	Moves up to 5 years of experience	Moves over 5 years of experience	Moves up to 5 years of experience	Moves over 5 years of experience
HC shortage	.013	-.105***	-.116***	-.142***
	(.02)	(.02)	(.02)	(.02)
HC redundancy	-.633***	-.686***	-.594***	-.652***
	(.02)	(.03)	(.02)	(.02)
Log employment of OCC1	.374***	.458***	.384***	.429***
	(.01)	(.01)	(.01)	(.01)
Log employment of OCC2	.382***	.465***	.399***	.442***
	(.01)	(.01)	(.01)	(.01)
Constant	-12.45***	-16.39***	-13.52***	-16.36***
	(.28)	(.32)	(.24)	(.31)
Ln(alpha)	.482***	.594***	.408***	.349***
	(.02)	(.02)	(.02)	(.03)
Log likelihood	-37116.08	-28046.09	-30744.04	-19487.13
Observations	13,806	13,806	13,806	13,806

Coefficients are reported. Robust standard errors in parentheses; Significant at *** 1%, ** 5%, * 10% level move directly from one job to another. This result fits the reasoning that among the young direct occupational switchers there are individuals who switch to more ambitious occupations where they incur high skill shortages and move upward on the career ladder. In line with this reasoning, a person should be less likely to move to a relatively complex occupation if he has been laid off than if he has been moved voluntarily. This is indeed supported by the empirical evidence: estimates of human capital shortage for indirect occupational switchers (layoffs) are always more negative than for direct occupational switchers.

People furthermore move more frequently to occupations where less human capital is left redundant. As in the case of human capital shortage, the correlations between the the number of observed moves and the human capital redundancy intensify for the more experienced groups. One interpretation is that more experienced labor is better positioned to protect their human capital from becoming redundant than less experienced labor. The results are also in line with earlier observations that more experienced people move to shorter occupational distances (Gathmann and Schönberg 2010). Similarly, those who move directly are in better position to prevent their human capital from remaining idle than those who were laid off from their previous occupation (i.e., compare the coefficients of human capital redundancy between models Ia and Ib, and between IIa and IIb).

4.4 Predicting the wage offer and the wage growth at the new job

In this section we explore whether human capital shortage and redundancy can predict the wage offered to employees who switch occupations, as well as the wage development at the new occupation.

4.4.1 Wage offers

For the purpose of illustration, let us frame the initial wage offer as the outcome of a wage bargaining situation where both the employer and the job candidate observe the candidate's qualifications, experience, ability, and (if applicable) his unemployment duration. If the candidate bargains for a position in an occupation that is simpler than his background occupation he would try to negotiate a starting salary above the average starting wage in that occupation. This is because he has qualifications that are richer than what is usually required for the position. If the employer finds these qualifications redundant, he would offer him the same starting salary that he would offer to a person, who, all else equal, comes from the same occupation as the one the candidate is applying for. Therefore, the effect of human capital redundancy on the instantaneous wage growth should be non-negative. In contrast, if the candidate applies for an occupation in relation to which he shows human capital shortage, the employer would opt for offering such candidate a lower starting salary than he would offer to a candidate coming from the same occupation, because of costs associated with on-the-job learning. Hence, we expect that the effect of human capital shortage on the wage offer is negative.

In order to evaluate this, we estimate a model where we regress our measures of human capital mismatch on the deviation of the individual's wage offer from the occupational mean wage offer received by first-time occupational entrants. We control for experience, age, education, unemployment length and year effects. We also include individual fixed effects regressions to control for ability-related biases. This approach is expressed in equation 4.4.

$$w_{iot} - \bar{w}_{ot} = \beta_1 Short_p + \beta_2 Redun_p + X_{it} + u_i + \varepsilon_{iot} \tag{4.4}$$

In 4.4, the left-hand side measures the individual wage offer deviation of occupational switchers from the occupational mean wage offer given given to people who enter the occupation without any labor market experience ($\bar{w}_{ot}$). The wage is observed for each person i who switches occupation o, at time t. On the right-hand side we have the human capital shortage and human capital redundancy that vary by occupational pair p. X_{it} stands for individual-specific time variant variables and for individual-specific time-invariant effects. Table 4.6 presents the OLS and the fixed effects results for the direct and the involuntary occupational moves.

Table 4.6: Explaining the wage offer at the new job

	Layoffs		Direct movers	
Dependent variable→	Dev. from occ. entrants' wage offer		Dev. from occ. entrants' wage offer	
	Model Ia	Model IIa	Model Ib	Model IIb
	OLS	FE	OLS	FE
HC shortage	-.028***	-.022***	-.035***	-.034***
	(.00)	(.00)	(.00)	(.00)
HC redundancy	.009***	.006**	.014***	.016***
	(.00)	(.00)	(.00)	(.00)
Experience	.030***	.042***	.051***	.057***
	(.00)	(.00)	(.00)	(.00)
Experience^2	-.001***	-.001***	-.001***	-.001***
	(.00)	(.00)	(.00)	(.00)
Age	-.003***	-.005**	-.003***	-.0001
	(.00)	(.00)	(.00)	(.00)
Education	.083***	.032***	.059***	.004
	(.00)	(.00)	(.00)	(.00)
Unemployment length	-.013***	-.006**		
	(.00)	(.00)		
Constant	.024	.259***	.100**	.221*
	(.02)	(.08)	(.04)	(.11)
R^2	.127	.064	.194	.159
Observations	58,961	36,168	132,795	98,260
Number of persons		16,156		39,659

Robust standard errors in parentheses. Significant at ***1%, **5%, and *10% level. HC shortage and HC redundancy are standardized to have mean 0 and S.D. 1.

In Table 4.6 one can identify few overarching patterns that match our expectations outlined above. First, independent of the type of move, human capital shortage is associated with lower wage offer at the job after the occupational switch. Second, human capital redundancy is consistently associated with a higher wage offer in all specifications. The inclusion of fixed effects does not reveal any substantial biases in the OLS coefficients.

4.4.2 Analysis of biases in the wage offer models

Ideally, we would like to work with a sample of plant closures because this type of presumably exogenous event results in employee displacement that comes as close as empirically possible to experimentally dislocated labor (see e.g., Gibbons and Katz 1991). Unfortunately, to this end there is no reliable identification of plant closures in the IABS. In fact, Hethey and Schmieder (2010) and Brixy and Fritsch (2004) show that the common strategy of taking the exit date of a plant in our administrative data as a plant closure is severely misleading. Therefore, in the analysis of wage offers we mainly focus on the sample of involuntary mobile. This is because we know that this is a sample of people who have been laid off from their last job[8]. In such a sample one expects that people accept the wage offer that exceeds the unemployment benefits. In contrast, voluntary movements reflect improvement in the value of the new job relative to the old one. Therefore, there should be strong self-selection into better job matches in our sample of direct moves. However, we also recognize that our sample of involuntary mobile is a sample that deviates from the general population. Layoffs may be of lower average ability than the general population. Furthermore, persons who manage to stay in the same occupation may be different from those who change occupations. For example, Neal (1995) argues that industrial switchers probably have less industry- specific skills than industrial stayers. A parallel can be made to the occupational dimension.

Moreover, people who move to similar occupations in terms of human capital shortage and redundancy may be systematically different from people who move to more distant occupations in terms of these measures.[9] In particular, we must address two selection problems: (1) among job switchers, occupational switchers may have less occupation-specific skills than occupational stayers, and (2) among occupational switchers, those who move to occupations where they incur higher human capital shortage (redundancy) may be of higher (lower) ability than those who move to

[8]This includes people who were laid off due to plant closures.

[9]For a comparable line of reasoning see Gathmann and Schönberg (2010, p. 24)

more similar occupations on these two dimensions. This is because we expect that high-ability people will tend to move to more demanding occupations-those where they face skill shortages, and low-ability people will tend to move to less demanding occupations-those for which they may even be over-qualified.

To solve the first selection problem we need to identify factors that affect the probability of switching occupations, but which do not affect the individual wage offer at the new job. Neal (1995) deals with a similar situation (p.660). He argues that the total number of jobs in an industry (in our case occupation) and the industrial (in our case occupational) employment growth of the pre-displacement industry (occupation) in the year of individual displacement are valid instruments in a wage growth regression. The rationale behind these instruments is that the search costs for laid off workers decrease with the employment size and the employment growth of an occupation making job switching within the same occupation easier. At the same time, in a competitive labor market, size and growth of an industry are unlikely to affect wages as they should reflect the marginal productivity of labor. Since job search tends to be geographically bounded, we define these measures for occupations in the individual's commuting area (see Gathmann and Schönberg 2010, p. 27 for such approach).

Second, the decision of switching to a more or less complex, or more or less related occupation is also endogenous. Therefore, we need to instrument our measures of human capital shortage and redundancy. In doing so, we follow Gathmann and Schönberg (2010) and, for each occupation of departure, we measure (a) the average human capital shortage in the commuting area based on the occupational structure in that commuting area and (b) the average human capital redundancy in the commuting area. Formally these measures are:

$$ADshort_{rto} = \sum_{o'} \frac{empl_{o'rt}}{empl_{rt}} Short_{oo'} \text{and } ADredun_{rto} = \sum_{o'} \frac{empl_{o'rt}}{empl_{rt}} Redun_{oo'}$$

Here, *empl* indicates the employment size, r is a region identifier, o is the occupation of departure o' the occupation of arrival and t is a year identifier. The intuition behind these measures is that due to the fact that search and reallocation costs increase with distance, people prefer to remain in the same commuting area. People living in areas offering a wide choice of related occupations will not have to make large jumps in terms of occupational shortage or redundancy. If an area has scarcity of related occupations people will be pressured to also choose among occupations that fit their skill profile worse.

Our identification strategy involves a combination of a Heckman (1979) and a 2SLS model (see e.g., Wooldridge 2002b, p. 567). In the first stage of the Heckman procedure we predict the occurrence of an involuntary occupational move as a function of a number of variables that are considered as exogenous in the wage offer regression[10] and all our instrumental variables. Using the prediction from the first stage we calculate the inverse Mills ratio. We then include the inverse Mills ratio in the 2SLS model (that is estimated only for occupational switchers) as an additional exogenous variable. Let us rewrite the model of interest 4.4 as:

$$y_1 = \mathbf{z_1}\boldsymbol{\delta_1} + \alpha_1 y_2 + \alpha_2 y_3 + u_1 \tag{4.5}$$

where y_1 is the deviation from the mean occupational entrants' wage offer, and y_2 and y_3 are our measures of human capital shortage and redundancy. $\mathbf{z_1}$ is a set of variables considered exogenous in the wage offer estimation. To this model we add a selection equation specified as

$$y_4 = 1(\mathbf{z}\boldsymbol{\delta_4} + v_3 > 0) \tag{4.6}$$

where in our case with three instruments $\mathbf{z}\boldsymbol{\delta_4}$consists of the size of the occupation of departure in the commuting area[11], $ADshort_{rto}$, $ADredun_{rto}$ and the exogenous variables from equation 4.5. Note that if our selection problem would have only

[10] This means that we include all variable that appeared in the wage offer regression with exception of human capital shortage and human capital redundancy.

[11] The growth of an occupation in a commuting area was not significant in the first stage probit model so we do not include it in our estimations.

consisted of a single selection-bias source, only one instrument would have sufficed in equation 4.6. y_4 takes value of 1 if a person changes the occupation and zero if a person changes job but not the occupation. Therefore, we estimate equation 4.6 for the full population of job switchers using a probit model. After obtaining $\hat{y}_4$, we calculate the inverse Mills ratio as $\hat{\lambda}_{i4} = \lambda(\mathbf{z_i}\hat{\delta}_3)$, which is a monotone decreasing function of the probability that an observation is selected into the sample. As a next step we estimate:

$$y_{i1} = \mathbf{z_{i1}}\delta_\mathbf{1} + \alpha_1 y_{i2} + \alpha_2 y_{i3} + \gamma_1 \hat{\lambda}_{i4} + e_i \tag{4.7}$$

by 2SLS where $\mathbf{z_i}$and $\hat{\lambda}_{i3}$ are instruments.

Table 4.7 presents the endogeneity-corrected models for layoffs. The dependent variable is the deviation from the mean occupational entrants' wage offer.

Table 4.7: Explaining the wage offer at the new occupation: bias-corrected results

Layoffs	
Dependent variable→	Dev. from occ. entrants' wage offer
HC shortage	-.039***
	(.00)
HC redundancy	-.003
	(.00)
Inverse Mills ratio	.042***
	(.01)
Experience	.028***
	(.00)
Experience^2	-.001***
	(.00)
Age	-.002***
	(.00)
Education	.084***
	(.00)
Unemployment length	.003
	(.00)
Constant	-.011
	(.02)
Observations	58,961

Results from a Heckman-2SLS model. Dependent variable: deviation from the occ. entrants' mean wage offer. Robust standard errors in parentheses. Significant at ***1%, **5% and *10% level.

Compared to the original OLS model (table 4.6, Model Ia) the human capital shortage coefficient is larger, and the human capital redundancy coefficient becomes insignificant. This means that the OLS overstated the effect of human capital redundancy and understated the one of human capital shortage. However, the endogeneity corrected estimates still point out in the direction of the expectations outlined at the beginning of section 4.4.1. The effect of human capital shortage on the wage offer at the new job/occupation is negative; one standard deviation increase of human capital shortage results in 4% lower wage offer. Furthermore, after the bias correction the effect of human capital redundancy is close to zero and is statistically insignificant. Therefore, the results suggest that employers do not reward employees for bringing skills that are not necessary for the job.

Since we have three instruments for three sources of bias we cannot test for overidentifying restrictions. However, we did test whether our instruments are weak. The partial R^2 of the first stage 2SLS estimations are .21 for human capital shortage and .17 for human capital redundancy. Therefore, we do not face weak instrument problem. Also, the t statistic of the coefficient of the size of the occupation in the commuting area in the first stage Heckman model is 4.53. Moreover, as evident in Table 4.7, the inverse Mills ratio is significant in the 2SLS specification. The complete tables of the first stage Heckman and the first stage 2SLS models can be found in appendix C, Tables C8 and C9.

4.4.3 Wage development at the new job

The initial human capital shortages and redundancies one brings from the old job may also affect the earnings development at the new job/occupation. Already in section 4.3 we suspected that people may move to occupations where they incur human capital shortage as a part of their career path (see discussion of Table 4.5, Model Ia). In such cases the human capital shortage measure may measure the learning potential implicit in the move to the new job. If higher shortages translate into more learning, the coefficient of human capital shortage may reverse and exhibit a positive effect on the wage growth in the job after the occupational change. To investigate this possibility we estimate equation 4.8:

$$(lnw_{io,t+n} - lnw_{iot})/t = \beta_1 Short_o + \beta_2 Redun_o + \varepsilon_{iot}. \tag{4.8}$$

Equation 4.8 indicates that we estimate the annual wage growth as a function of the measures of human capital asymmetries and a set of controls[12] (not noted in 4.8). We study the annualized wage growth after 1, 3 and 5 years at the new occupation. We focus on the sample of direct occupational switchers because this is where we expect that people intentionally move to more ambitious occupations as a part of their career progression. Moreover, we expect that these types of moves are more common in the early years on the labor market and therefore we distinguish between a sample of those who change occupations within the first 5 years on the labor market and those who change occupations later. Table 4.8 contains the results of these estimations.

As suspected, human capital shortage does reverse the sign in the prediction of the wage development at the new occupation. This is evident in models IIa, IIIa IIb, and IIIb. Even more in line with the expectations outlined above, the coefficients of human capital shortage are larger for the sample of less experienced labor than those in the sample of more experienced labor (.003 vs. .002).

The effects noted in Table 4.8 diminish once we control for individual fixed effects. One possible interpretation of this is that if our claim that human capital shortage captures learning at the new job is correct, such learning only pays off through wage growth if persons are of certain ability. One direct implication of such result would be that moves to more ambitious occupations are only justified for people of sufficient ability and if there is an ability-ambition mismatch this will also be reflected in the wage development at the job.

4.5 Skill experience and wages

4.5.1 Construction of skill experience

Until now, we have used the skill-vectors only to characterize occupational pairs. However, we can also use them to construct an experience vector that reflects employees' complete work history. For this purpose, we add up all skill vectors corresponding to the jobs an individual held in the past. Let $e_{t,o}$ represent the length in

[12]The controls include: age, experience, education and a set of year dummies.

Table 4.8: Explaining the wage development at the new occupation

	Direct moves:≤5 yrs of experience			Direct moves:>5 yrs of experience		
	Model Ia	Model IIa	Model IIIa	Model Ib	Model IIb	Model IIIb
Dependent variable→	Wage growth after 1yr	Wage growth after 3 yrs	Wage growth after 5 yrs	Wage growth after 1yr	Wage growth after 3 yrs	Wage growth after 5 yrs
HC shortage	.0002	.003***	.003***	.0001	.002***	.002***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
HC redundancy	.001**	.001	.001**	.001	.001***	.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Education	.002***	.003***	.003***	-.001	.001***	.002***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Age	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Experience	-.004***	-.004***	-.003***	-.001***	-.001***	-.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Year dummies	yes	yes	yes	yes	yes	yes
Constant	.055***	.076***	.060***	.049***	.033***	.035***
	(.01)	(.01)	(.00)	(.01)	(.01)	(.00)
R^2	.026	.094	.147	.038	.108	.150
Observations	43,804	25,962	15,743	26,107	23,386	13,926

Robust standard errors in parentheses. Significant at ***1%, **5%, *10%. HC shortage and HC redundancy are standardized to have mean 0 and SD 1.

years of an individual's t^{th} employment spell in occupation o. We can now recursively define the total skill experience of the individual at the end of this t^{th} spell as:

$$S\vec{E}_t + S\vec{E}_{t-1} + e_{t,o}\vec{v_o}^n \tag{4.9}$$

where we normalized the skill-vector of occupation o by the average length of all occupational skill-vectors $\vec{v_o}$to arrive at the normalized $\vec{v}_o^n$. As a consequence, the length of the skill experience vector is the total experience acquired in past jobs weighted by the complexity of the occupation in which the experience was acquired. That is, the unit of measurement is complexity weighted years, where one unit represents the experience one would acquire in an occupation of average complexity. This means that the skill experience vector will grow fastest in complex occupations, which require much education.

The skill experience vector can now be compared to the skill-profile of an individual's current job. As before, we will use vector decomposition to derive a component parallel to the current occupation's skill-vector and a component perpendicular to it. We label the former component 'useful human capital' and the latter 'useless human capital.' Figure 4.5 depicts this decomposition graphically.

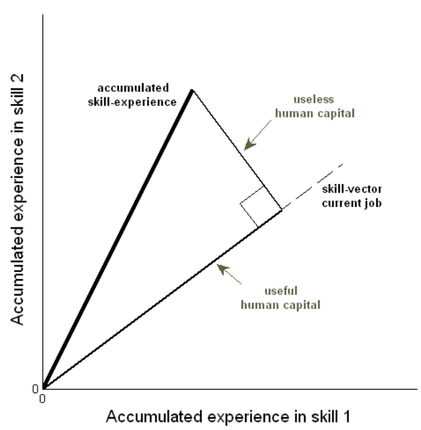


Figure 4.5: Decomposition of the skill experience into a useful and a useless component

The skill experience variables at spell t can now formally be defined. Using the same trigonometry as in equation **??**, an individual's useful human capital at spell is:

$$HC_{useful_t} \frac{\vec{SE} \cdot \vec{v_o}}{||\vec{SE_t}||||\vec{v_o}||} ||\vec{SE_t}|| \tag{4.10}$$

where $||\vec{x}||$ represents the length of a vector $\vec{x}$ and $\vec{v_o}$is the current occupation's skill vector. Using Pythagoras, we obtain the useless component of human capital:

$$HC_{useless_t} = \sqrt{||\vec{SE_t}||^2 - HC^2_{useful_t}} \tag{4.11}$$

4.5.2 Returns to skill experience

In what follows, we will use the variables constructed in subsection 4.5.1 to estimate the returns to useful and useless skill experience. As here we only want to sketch how the skill experience variables could be used, we will use OLS and fixed effects estimates and ignore endogeneity and censoring issues.

Based on educational attainment, we split up the sample into low-skilled, medium-skilled and high-skilled sub-samples[13]. The problem of censoring is relevant for the high-skilled sample, where censored wages account for about 25% of all spells. For the low-skilled and medium-skilled subsamples, censoring is under 5% and can therefore be ignored. For this reason, we will focus our discussion on the findings in these two samples.

The outcomes of the regression analyses for low- and medium-skilled employees are reported in Tables 4.9 and 4.10.[14] Models Ia shows the baseline OLS estimates where the log of wage is regressed on experience, experience squared, occupational experience (i.e., the number of years an employee spent in his current occupation),

[13]Low-skilled employees are those with no formal education; medium-skilled are employees with secondary education including those with vocational training. High-skilled employees have college or university education.

[14]Appendix C contains the descriptive statistics and the correlations for the set of variables used in these estimations.

and plant experience (i.e., the number of years an employee spent in his current plant). The specification also includes occupation and year dummies.

Our analyses confirm Gathmann and Schönberg's (2010) finding that there are significant returns to useful skill experience. These returns easily surpass those of occupational tenure and of plant tenure. However, OLS Models IIa and IIIa slightly overstate these returns in the low-skilled sample and understate them in the medium-skilled ones when compared to fixed effects estimates (Models IIb and IIIb).

However, also 'useless human capital' generates positive returns. In the low-skilled sample, these returns are only about a quarter of the returns to useful human capital. In the medium and high-skilled samples, the returns are more substantial and sum up to 44% of those of 'useful human capital.' We believe that the positive effect of useless human capital is due to the fact that our skill experience variables partly reflect the complexity of pervious jobs. When we replace the useless human capital and useful human capital variables by the ratio of useless-to-useful human capital (Models IVa and IVb), we find a negative effect in all specifications. This indicates that useless human capital is indeed less valuable than is useful human capital. Therefore, people who build their career path such that they stay within a cluster of skill-related occupations earn, on average, better *ceteris paribus.*

Nevertheless, as elaborated in Gathmann and Schönberg (2010) there are several sources of bias in these estimations and further scrutiny is needed before we can conclude the effects of useful and useless on wages.

Table 4.9: Returns to skill experience (low-skilled)

	OLS				FE			
	Model Ia	Model IIa	Model IIIa	Model IVa	Model Ib	Model IIb	Model IIIb	Model IVb
Useful experience		.032***	.036***			.027***	.031***	
		(.00)	(.00)			(.00)	(.00)	
Useless experience			.009***				.008***	
			(.00)				(.00)	
Useless exp./useful exp.				-.125***				-.039***
				(.00)				(.00)
General experience	.048***	.024***	.017***	.050***	.050***	.029***	.023***	.050***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
General experience^2	-.002***	-.002***	-.002***	-.001***	-.001***	-.001***	-.001***	-.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Occupational experience	.005***	.0007***	.004***	-.0004*	.001***	-.002***	.0003	-.0003
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Plant experience	.010***	.010***	.010***	.009***	.003***	.003***	.003***	.003***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Occupation/year dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	4.236***	4.229***	4.230***	4.290***	4.358***	4.368***	4.371***	4.411***
	(.02)	(.02)	(.02)	(.02)	(.03)	(.03)	(.03)	(.03)
R^2	.415	.416	.417	.410	.246	.248	.248	.230
Observations	375,849	375,849	375,849	345,396	375,849	375,849	375,849	345,396
Number of persons					72,952	72,952	72,952	62,595

Dependent variable: ln(wage). Robust standard errors in parentheses. Significant at ***1%, **5% and *10% level. All experience variables are expressed in years (or experience years). Plant and occupation experience calculate total years of experience in the present occupation and plant, regardless of whether this experience was interrupted by spells in different occupations or plants. Censored wages (2.8% of all spells for low-skilled, 5.0% for medium-skilled)

Table 4.10: Returns to skill experience (medium-skilled)

(b) Medium-skilled

	OLS				FE			
	Model Ia	Model IIa	Model IIIa	Model IVa	Model Ib	Model IIb	Model IIIb	Model IVb
Useful experience		.028***	.032***			.035***	.043***	
		(.00)	(.00)			(.00)	(.00)	
Useless experience			.013***				.019***	
			(.00)				(.00)	
Useless exp./useful exp.				-.100***				-.024***
				(.00)				(.00)
General experience	.047***	.026***	.016***	.050***	.051***	.022***	.007***	.053***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
General experience^2	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Occupational experience	.005***	.001***	.005***	.001***	.003***	-.002***	.005***	.003***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Plant experience	.005***	.005***	.005***	.005***	.001***	.001***	.001***	.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Occupation/year dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	4.271***	4.278***	4.281***	4.314***	4.375***	4.388***	4.399***	4.437***
	(.02)	(.02)	(.02)	(.02)	(.03)	(.03)	(.03)	(.03)
R^2	.395	.398	.398	.393	.396	.402	.403	.391
Observations	494,747	494,747	494,747	481,315	494,747	494,747	494,747	481,315
Number of persons					137,123	137,123	137,123	131,707

All notes as in Table 4.9

4.6 Conclusions

We provide empirical evidence that there are considerable asymmetries to be reckoned with when studying human capital transferability in job switches. We construct a set of asymmetric measures of cross-occupational human capital or skill mismatches and use these to study job switching across occupations. These measures provide information above and beyond existing symmetric measures of occupational distance. We additionally propose a measure of skill experience that captures the cumulative skill formation over the course of individuals' occupational history. The measure of skill experience further allows us to disentangle useful from useless skill accumulation relative to the current occupation.

Our measures show superior predictive power with respect to between - occupational moves compared to existing measures. Furthermore, their asymmetric nature allows us to shed light on a hitherto neglected aspect of occupational switches: the direction of the switch. Occupations do not only differ from one another in terms of their skill profiles, but they also require these skills at different degrees of complexity. As such, occupations can share a similar set of skills, but may differ in their position on what could be termed as occupational complexity ladder. We show that this asymmetry has profound effects on between-occupational moves and wage dynamics. First, people sort into jobs that limit their human capital losses, especially in voluntary or, to be more precise, job-to-job movements. At the same time, few cross-occupational job switches are observed that are associated with high human capital shortages. This effect holds for both, involuntary and voluntary occupational switchers with an exception of people with few years of labor market experience that voluntarily change occupations. This group seems to choose higher levels of human capital shortage than other groups. That behavior is punished in the short term: having a human capital shortage results in a lower wage offer at the new job. However, this initial wage loss associated with an ambitious career path is compensated by above average wage growth at the new job, which may reflect an effect of steeper learning curves.

Second, using our proposed measure of skill experience, we show that even after controlling for plant, occupation, and general experience, skill experience remains the dominant predictor of wages. Additionally, although both the useful and the useless component of the skill experience correlate positively with wages, wages are lower the larger the ratio between the useless and the useful component. In future research, this detailed representation of individual's life-time accumulated skills might help us gain understanding of how some individuals build up skill portfolios to the benefit of lifetime earnings and others do not.

Skill experience vectors may have a number of applications that support policy makers in dealing with changes in the economic structure of countries. For instance, they could be used to investigate the effects of structural change on the economy-wide destruction of human capital. That is, it is possible to construct a vector that captures the current labor force's skill profile and compare this to a vector that represents the required skills in a hypothetical, post structural change economy. This would allow identifying which parts of the labor force that are most likely to suffer from changing skill requirements and which are best positioned to benefit from them.

Chapter 5

Discussion, policy lessons and further research

5.1 Discussion of the main findings

The main findings of this thesis can be structured as: (a) findings about the trends and the recent state of the skill composition of the economy, (b) findings about the factors of the skill demand changes, (c) findings about the consequences of skill mismatch for occupational switchers. This chapter summarizes each of these categories of results, discusses the policy-relevant information that they provide, and the questions for further research which they motivate.

5.1.1 Occupational and skill structure trends

One way of analyzing the structural change that marked the last several decades of developed economies is by investigating the shifts in the occupational structure and the work task content of jobs. Doing so, at the level of economy we find that occupations that make intense use of complex cognitive, sales-related, and care-related tasks increased their presence in the economy, while occupations that make intense use of tasks that can be explained through step-by-step (explicit or codifiable) procedures lost employment share. At the level of the individual worker, performing explicit work tasks is associated with higher layoff risk. This association is observed even when focusing on individuals that belong to the same sector or have equal levels of education. Furthermore, while performing abstract or interactive tasks mainly corresponds with higher job security in the first two periods that we examined (1979 and 1998/1999), the relationships are weaker in the last period observed (2005/2006). Therefore, it would be interesting to further investigate whether reduced job security has also spread to these occupations, becoming a general phenomenon in more recent years.

Comparing the changes in the work content across sectors reveals notable differences among them. Neither all sectors intensified the performance of abstract and interactive tasks, nor did all sectors release labor that performs explicit tasks. Some even enhanced the employment of such labor. Therefore, the aggregate trend toward labor that performs complex cognitive tasks and away from labor that performs explicit tasks conceals certain industry peculiarities in the demand for heterogeneous labor.

5.1.2 Factors of skill structure changes

The dominant theory that explains the aggregate trend toward complex cognitive and interactive work content and away from explicit or codifiable task content is a nuanced theory of skill-biased technological change. It claims that code-based technologies substitute tasks that can be exhaustively explicated through step-by-step instructions (routine, or as we refer to them, explicit tasks), and complement non-routine cognitive and manual tasks (e.g., abstract and interactive tasks). Another dominant theory is a theory of international outsourcing which predicts that expanding world labor markets force countries to specialize in their core competences. Developed countries specialize in abstract or problem-solving tasks, although this competitive advantage is unstable because many low cost countries rapidly invest in their competences. Interactive tasks may not be core competence, but are difficult to outsource because they involve frequent and face-to-face contact with customers and clients. Explicit tasks are easily taught to foreign labor and are therefore at highest risk of outsourcing.

The findings of chapter 2 are in line with the nuanced version of skill-biased technological change theory because even within identical educational levels and sectors employees who perform explicit tasks have lower job security. However, in this chapter we do not measure technology explicitly. In chapter 3 we estimate IT technology-labor elasticities for twelve sectors. The results are at odds with the claim that technological change is a driving force behind the decline of occupations that make frequent use of codifiable tasks. Nevertheless, these results must be read with much caution (see subsection 3.5.2 and section 5.2). When it comes to outsourcing, we find that it is associated with downsizing of explicit tasks in four out of twelve industries; in three industries also abstract (nonroutine cognitive) labor is at risk of outsourcing. These latter findings are in line with an outsourcing theory (see Blinder 2006, 2009) which claims that not only occupations that execute explicit tasks are at risk of outsourcing, but also those that provide intellectual services for which intense personal contact with customers is not necessary.

5.1.3 Human capital mismatch

When individuals change occupations, they move to those occupations where relatively little of their skills remain idle. Those who are forced to move to jobs that leave part of their human capital idle are not rewarded for the redundant skills. This would mean that if skills are rendered obsolete by, for instance, technological innovation, the future individual earnings will be reduced proportional to the level of skill redundancy. Individuals also avoid moving to jobs that require acquisition of new skills. Those who switch to occupations where they have to upgrade their human capital are initially penalized for their skill shortage through lower wage offers, but later on experience steeper wage growth on the new job.

We further find that staying within occupations that have high skill overlap positively contributes to wages. This latter result confirms the conclusion derived by Gathmann and Schönberg (2010): human capital is more general than previously thought. Skills are transferable across occupations if occupations require overlapping sets of skills and this transferable human capital is reflected positively in individuals' earnings.

This leads us to make two observations that are relevant for structural change research. On the upside, human capital is more skill than job specific, meaning that individuals do not necessarily have to stay in the same job or occupation in order to maximize long-term earnings: it suffices that they stay within related occupations. On the downside, skill obsolescence is what makes structural change costly: the more skill disruptive an innovative change is, the worse off are employees in terms of earnings.

5.2 Novelty, some methodological contributions and limitations

The thesis draws attention to the value of analyzing the content of human capital in economics. Such an approach is rather uncommon in economics. We show that the approach can contribute to an understanding of how structural change can relocate or destroy the demand for certain skills while increasing the demand for others. This reveals many aspects that remain hidden using commonly used measures of human capital such as educational attainment. The approach additionally deepens our understanding of how people move in an economy and why wages develop in certain ways.

A further contribution is the introduction of asymmetries in the transferability of human capital. To measure this concept, we propose two novel measures: human capital shortage and human capital redundancy. We will discuss below that these measures can find wider application than what has been demonstrated in this thesis.

Furthermore, we extend the measure of task experience proposed by Gathmann and Schönberg (2010), by introducing a measure of skill experience. The main advantage of the skill experience measure is that it can be decomposed into skill experience that is useful and skill experience that is useless in an individual's current occupation.

Apart from contributions, there are also a number of limitations to the work presented so far. The most worrisome is the way IT-labor and outsourcing-labor relations are modeled in chapter 3. In labor economics, substitution effects among production factors have been modeled empirically in several ways. Most of them are based on production theory that imposes restrictions on the empirical specification. This is as well the case with the translog function where a cost minimizing firm with a translog production function is assumed. However, these restrictions may not hold in reality and effects may be identified based on too rigid assumptions. Therefore, in order to establish robust findings about the IT-labor and outsourcing-labor relations we will have to apply other approaches as well. Until then, the results should be seen as suggestive and not definite.

Another limitation arises in the empirical analysis of the skill experience measures in chapter 4. Here, we still need a proper identification strategy which we relegate to future research.

Further limitations stem from the data characteristics. For instance, using a longer panel in chapter 3 should allow us to account for the lag structure between IT investments and labor flows and the recently added questions to the survey should make it possible to distinguish between domestic and international outsourcing.

5.3 Policy lessons

We have shown that outsourcing may have less predictable effects on labor demand in developed countries than do code-based technologies. The opening of world labor markets may lead to reallocation of labor of much more diverse character to low-cost points. That is, firms may not only outsource explicit task intensive processes such as assembly line, but they may as well outsource intellectually intensive tasks which can be electronically conveyed on a distance without substantial quality decay. The continuing steep fall in the prices of communication technologies and their proliferation in developing countries will only support the international competition between labor. Predicting the types of skills that will be outsourceable in future is extremely difficult because the potential for outsourcing does not only depend on developments in leading countries, but mainly depends on developments in low-cost countries. The faster developing countries catch up in the upgrading of their skills, the sooner it may happen that more complex firm functions are outsourced abroad.

The results in chapter 3 as well as other studies of German outsourcing patterns (e.g., Geishecker 2006b) generally support the offshoring theory of Blinder (2006, 2009). Occupations whose work-content requires intense customer contact will be better-protected from international labor competition than occupations whose work output can be transmitted without loss of information over distance. Therefore, the international competition for talent may in particular affect jobs such as programmers, statistical analysts and web-designers. The kaleidoscopic character of skill-based competitive advantage and the footloose capital behavior mean that today, more than ever, the quality of education can ensure that jobs which provide high value-added are kept at home. Such education should be made available to the complete potential of students, leaving no room for discrimination of any kind. Therefore, this research speaks in favor of initiatives such as the 2010 amendment of the Federal Training Assistance Act (BAföG) that increases the pool of BAföG eligible recipients.

Both, the opening to world markets and technological advances in the codification of knowledge make the predictions of future labor demand less certain. When labor markets are uncertain, the investment into more general human capital is more favorable than the investment in specific human capital. Individuals who have acquired more general skills have skill overlap with larger number of occupations and may therefore have fewer hurdles in the search of new employment. Additionally, fewer of their skills will remain idle if they are forced to switch to another occupation. Therefore, one policy lesson is that during their education, people should be taught more general skills besides the specialized ones necessary for the job. Moreover, possibilities for requalification should be made available at any stage of the career. This is in particular relevant in a country like Germany where large part of the working population obtains highly specialized vocational training. In the dual system of education students are encouraged to match their skills and knowledge with the most current needs of the firms and organizations in which they are engaged during their training. Although, there are certain advantages to this strategy, a problem arises if current skill needs might be very different from those of the future. In that case, highly-specialized trainees are at a disadvantage compared to candidates who have obtained more general set of skills and knowledge.

Based on the results obtained in chapter 4 we derive another policy lesson which regards the type of requalification that one should obtain in a case of a job loss without an opportunity to return back to the current occupation. In order to reduce the human capital redundancies and the forgone earnings of people, individuals should be requalified to occupations that are as close to their previous occupational profile as possible as long as such jobs in related occupations are in demand.

At the regional level structural change means alteration of the industry structure. There are myriad examples where reallocation or closure of a single large plant can leave hundreds or even thousands unemployed in a region. Through marketing such regions attempt to attract new businesses. One major location criteria of firms is access to adequate labor force. For instance, Neffke and Henning (2010) find that regions attract industries with similar human capital needs as those of the region's current core industries. The proposed measures of skill mismatch, in particular the one of skill shortage can be used by regional planning units to assess the proximity of current (active and in particular inactive) labor force skills to those skills required by industries interested in investing into the region. By making information about the skill structure and the skill proximity of the available labor visible to interested firms regions can help firms make better informed investment decision. Such information can for instance help them estimate the training costs of the employees.

A dominant debate in the German labor market policy in the last few years is about the shortage of skilled labor (Fachkräftemangel). While the Federal Agency for Civic Education (BPB) urges for foreign labor inflow, the Institute for Employment Research (IAB) and the German Employment Agency (BA) warn that a notable share of the talent in Germany can be found among the 7.6%[1] unemployed (Frankfurter Allgemeine 2010). However, to this end no one reports a clear picture about the size of this talent potential. One way to analyze it is to look at the occupational structure of the unemployed. Nevertheless, we propose a more informative approach. The skill experience vectors of section 4.5 can also be constructed using occupational history information of the unemployed and non-participating labor. The cumulative skill experience should serve as a good approximation of the underlying skill potential. This will inform policy makers about the dormant skills of the unemployed and the potential for their activation.

Moreover, a cumulative skill vector of the complete German labor force (active and inactive) can be compared to a projected skill vector constructed with information about labor shortages by occupation. The analysis of the skill discrepancies between the current and the demanded skills can inform which areas might warrant extra attention in education policy. In a similar way, one can construct region-specific skill experience vectors and analyze the region-specific skill shortages.

5.4 Further research

Trend toward more frequent moves between less related occupations

Besides the trend toward more frequent occupational switching of some groups (see Figure 1.1), we also observe a trend of increasing average occupational distance in the economy in the period 1976-2004. The average occupational distance that

[1] As of July 2010 (Bundesagentur für Arbeit 2010)

people made in the 1970 was .15[2], almost .16 in the 1980s, almost .17 in the 1990s and over .18 after 2000.[3] The trend is present in all age and education groups with exception of college and university graduates. One hypothesis is that the trend is driven by changes in the specialization patterns of occupations: nominally identical occupations have been more specialized in the past than today which makes it less costly to switch to more distant occupations. If the pattern of specialization did not change over the observed period, increased occupational distance of occupational switchers implies that the costs of human capital redundancy increased over time.

The same time period witnessed increases in the per pupil/student educational expenditures. The result of a situation where rigid division of tasks among occupations is accompanied by high individual investments in human capital, frequent occupational changes, and common instances of switching to less related occupations will necessarily result in large costs of human capital redundancy. The German educational system is notorious for its specialized education in comparison to other countries (Hall and Soskice 2001; Goldin and Katz 2009). This might have changed. Some of the described trends may be results of decreased specialization.

Evaluation of requalification programs in Germany

One salient pattern that both we and Gathmann and Schönberg (2010) find is that, in long run, in terms of earnings, it pays off to stay within a related skill space. Similarly, Kambourov and Manovskii (2009) and Polataev and Robinson (2008) find support that occupational relatedness is much more important than industrial relatedness for the earnings profile of displaced workers. There is anecdotal evidence that requalification programs in Germany do not incorporate this aspect of occupational change in their requalification decisions. One important next step is to understand how matching in requalification programs takes place and whether there is room for

[2]Here we are using the measure proposed by Gathmann and Schönberg (2010). It ranges between 0 (same occupation) and 1 (no skill overlap).

[3] Notice that this measure of occupational distance does not reflect educational differences in occupations and is therefore not driven by the educational upgrading in the economy.

improvement.

Are growing jobs lovely jobs?

Here we ask which jobs are desirable from the human point of view and whether the economy is adapting toward or away from such jobs? Using information on what people do at their jobs in terms of tasks, pay, level of social interaction, stress, job stability and other determinants of job satisfaction, we would like to observe whether the economy is moving toward "lovely" or "lousy" jobs (to use the terminology of Goos and Mannig 2007). While the growing service jobs contain far more social interaction (which is found to be intrinsically rewarding) than the typical manufacturing jobs, they may bring along lower job security and often better pay.

Skill structures of Eastern and Western Germany, convergence and consequences for labor productivity

The QCS includes East Germany since 1991/1992. One policy-relevant question is to understand why East Germany lacked and still lacks behind the labor productivity in West Germany (e.g. Fritsch and Mallok 1994, Klodt 2000). We would like to analyse the discrepancies in the skill portfolios of East and West Germany from shortly after the reunification until the latest period available, and examine whether differences in the types and the combination of skills within comparable industries can explain some of the labor productivity divergences. We should also be able to see whether skill convergence took place and whether it leads to convergence in the labor productivity.

Misfits and Stars[4]

In chapter 4 we distinguished between useful and useless human capital. We wonder whether useless human capital is really useless to all people. One could imagine that there are roughly two types of individuals that acquire large amounts of useless human capital. On the one hand, there are the people that are unable to find a job that fits their profile. These people keep wandering from one occupation to the next without building up any coherent set of skills. On the other hand, there are people who simply see commonalities among jobs that remain hidden to other people. These people are in fact able to combine experiences from a wide range of contexts, often generating novel solutions to the problems they encounter. If this is indeed the case, then the variance of wages should increase as the ratio of useless-to-useful skill experience increases.

As an exercise we plotted the variance in wages for equally sized age categories for different levels of useless-to-useful skill experience. We see that wage variances normalized by the average wage levels steadily increase for higher values of the useless-to-useful human capital ratio. This suggests that there is indeed a higher risk involved in building up large amounts of useless skill experience. Whether this is truly due to the fact that individuals differ in their capacity to combine and learn from very different experiences deserves further scrutiny. However, our skill-decomposition of human capital does show some promising results in this direction.

Have the determinants of wages changed over time?

For a set of nominally identical variables: age, age squared, education, around 120 occupational and 16 industry dummies in a sample of full-time employed males in West Germany it becomes more and more difficult to predict wages over time. Figure 5.1 plots the pseudo R squared from a censored wage regression which was estimated separately for each year. We see that the share of the variance that these variables can explain falls from 54% in 1975 to 32% in 2004. This observation may simply be an artefact: the occupational, educational and industry classification used most likely

[4] Åstebro, Chen, and Thomson (2010) use this terminology to label self-employed which are drawn from the left (misfits) and the right (stars) tail of the wage distribution.

capture far better the commonalities within occupational, educational and industry groups in the years closer to their definition than in later years. This we can test with availability of updated classifications. However, if the observation of decreased power of the Mincer wage equation persists after correcting for errors stemming from the classifications, it would be interesting to investigate which factors of wage determination play larger role today than they did in the past.

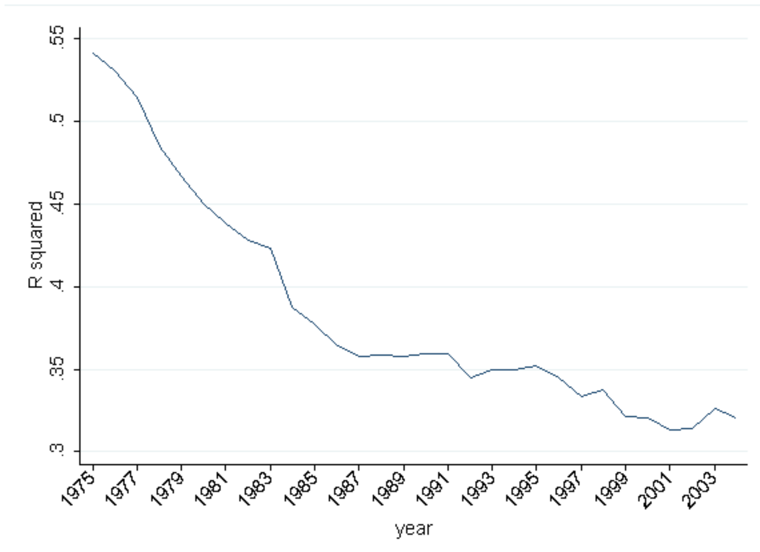


Figure 5.1: Falling predictive power of common wage determinants
Source: IABS Regional (1975-2004)

Deutschsprachige Zusammenfassung

Ausgangspunkt der vorliegenden Arbeit ist die Beobachtung, dass in den vergangenen Jahrzehnten in entwickelten Volkswirtschaften ein Strukturwandel weg vom verarbeitenden Gewerbe hin zum Dienstleistungssektor beobachtet werden konnte. Die Dissertation beschäftigt sich mit den Konsequenzen dieses Veränderungsprozesses für die Berufs- und Humankapitalstruktur in Deutschland. Dabei stehen insbesondere Qualifikationen (skills) als wesentliches Element von Humankapital im Mittelpunkt der Dissertation, da sich Erstere im Vergleich zu Fähigkeiten und allgemeinem Wissen einfacher messen lassen.

Das einführende Kapitel fasst die bisherige Literatur auf dem Gebiet von Arbeit und Humankapital aus wirtschaftshistorischer Sicht zusammen. Besondere Beachtung wird Forschung zum Verhältnis von Arbeit und Technologie beziehungsweise Arbeit und Outsourcing geschenkt, wobei unter Letzterem die Auslagerung von Arbeitsplätzen an Drittunternehmen im In- oder Ausland verstanden wird. Ein weiterer Schwerpunkt des ersten Kapitels ist ein Überblick zu Untersuchungen, die sich der Frage nach der Transferierbarkeit von Humankapitel im Falle eines Arbeitsplatzwechsels widmen.

Das zweite Kapitel „Occupations at risk: The task content and job security“ ist dadurch motiviert, dass noch in den 1980er Jahren im Allgemeinen die Auffassung vorherrschend war, Arbeitnehmerqualifikation und Jobaussichten würden, zumindest in entwickelten Volkswirtschaften, einen positiven Zusammenhang aufweisen. Als

Begründung angeführt wurde zum einen, dass (technologische) Innovationen komplementär zu Qualifikationen sind, und zum anderen, dass aus der zunehmenden Öffnung internationaler Märkte eine Spezialisierung auf Güter und Dienstleistungen folgt, deren Produktion ein vergleichsweise hohes Maß an Qualifikationen erfordert. Allerdings zeigen neuere Studien, dass in entwickelten Ländern in den vergangenen zwei Dekaden Arbeitsplatzabbau im Wesentlichen auf die mittlere Einkommensschicht entfiel. Demgegenüber haben gering entlohnte Arbeitsplätze in den letzten 20 Jahren vielerorts gar an Bedeutung gewonnen. Eine mögliche Erklärung für diesen Befund rekurriert auf das Maß an Kodifizierbarkeit einer Tätigkeit. Die Kodifizierbarkeit einer Tätigkeit bemisst sich in der vorliegenden Arbeit danach, inwieweit die Durchführung der entsprechenden Tätigkeit bis in alle Einzelheiten vorgeschrieben ist, also ihr Inhalt formal artikuliert werden kann. Es ist zu vermuten, dass eine Tätigkeit, die durch hohe Kodifizierbarkeit gekennzeichnet ist, auf der einen Seite vergleichsweise einfach in Programmcodes und -routinen überführt werden kann (Substituierbarkeit durch Technologie gegeben) und auf der anderen Seite ausländischen Arbeitnehmern mit relativ geringem Aufwand beigebracht werden kann (Anfälligkeit für Outsourcing).

Die Hypothese, dass der Grad der Kodifizierbarkeit einer Tätigkeit und Arbeitsplatzsicherheit negativ korreliert sind, wird am Beispiel von (West-)Deutschland im Zeitraum 1975-2004 überprüft. Zu diesem Zweck werden die Beschäftigten-Stichproben des Institutes für Arbeitsmarkt- und Berufsforschung (IAB) mit der Qualifikation und Berufsverlauf Befragung des Bundesinstituts für Berufsbildung (BIBB) und des IAB kombiniert, wobei Letztere Aufschluss über die Intensität von Qualifikationen in verschiedenen Berufen liefert. Es zeigt sich, dass in der Tat der Beschäftigtenanteil von Berufen mit einem hohen Anteil an kodifizierbaren Tätigkeiten im Zeitablauf abgenommen hat, und zwar zugunsten von Berufen, die sich hauptsächlich durch interaktive (das heißt auf Dienstleistungen bezogene) und problemlösungsorientierte Tätigkeiten auszeichnen. Ein monotoner Zusammenhang zwischen Lohnsätzen und Beschäftigungswachstum, der wie oben erwähnt noch in den 1980er Jahren unterstellt wurde, lässt sich deshalb nicht beobachten, da Berufe mit hohem Anteil an kodifizierbaren Tätigkeiten oftmals in der Mitte der Lohnsatzverteilung angesiedelt sind. Darüber hinaus konnte mit Hilfe einer ökonometrischen Analyse gezeigt werden, dass Arbeitnehmer in diesen, durch ein hohes Maß an Kodifizierbarkeit gekennzeichneten, Berufen einem vergleichsweise hohen Risiko eines Arbeitsplatzverlustes ausgesetzt sind, wobei dieses Ergebnis auch dann robust ist, wenn auf individueller Ebene für Bildung und Industriezugehörigkeit kontrolliert wird.

Bisherige Literatur, die sich mit dem Verhältnis von Arbeit und Technologie beziehungsweise Arbeit und Outsourcing befasst, schenkt üblicherweise der Möglichkeit keine Beachtung, dass dergestalte Zusammenhänge industriespezifisch sind und daher ein rein makroökonomische Betrachtung zu kurz greifen könnte. Erheblicher Forschungsbedarf besteht darüber hinaus dahingehend, wie die Nachfrage nach Qualifikationen auf Änderungen in der Technologie vis-à-vis Outsourcing reagiert. Beide Aspekte werden in Kapitel drei „Technology, outsourcing and the demand for heterogeneous labor: Exploring the industry dimension“ aufgegriffen. Als Datenbasis zur Verwendung kommen die Qualifikation und Berufsverlauf Befragung, die auch im vorangegangenen Kapitel zwei genutzt wird, sowie der Linked Employer-Employee Paneldatensatz des IAB. Dies ermöglicht die Schätzung von Technologie-Arbeit- sowie Outsourcing-Arbeit-Elastizitäten für zwölf Industrien in Deutschland für die Periode 2000-2004. Wie schon in Kapitel zwei wird Arbeit mit Blick auf die Intensität, mit der eine bestimmte Qualifikation zum Einsatz kommt, als (hauptsächlich) kodifizierbar, interaktiv und problemlösungsorientiert klassifiziert. Als Maß für Technologie dient der Kapitalstock an Informations- und Kommunikationstechnologie.

Im Ergebnis lassen sich keine inter-industriellen Unterschiede in den Technologie-Arbeit-Elastizitäten feststellen. Ebenso wenig zeigen sich Unterschiede dahingehend, wie Technologie die Nachfrage nach verschiedenen Arten von Arbeit beeinflusst. Demgegenüber lässt sich eine dergestalte Symmetrie im Falle von Outsourcing nicht beobachten. In den Industrien, in denen Outsourcing signifikant auf die Arbeitsnachfrage wirkt, zeigt sich, dass kodifizierbare Arbeit vorrangig negativ beeinflusst wird. Allerdings ist zu konstatieren, dass in einigen Industrien auch Tätigkeiten, die vorrangig problemlösungsorientiert sind, einen negativen Zusammenhang mit Outsourcing aufweisen. Dagegen ist die Nachfrage nach interaktiver Arbeit entweder positiv von Outsourcing betroffen oder bleibt gänzlich unbeeinflusst.

Der Beitrag des vierten Kapitels „Human capital mismatch along the career path" ist zum ersten ein theoretischer Ansatz zur Messung der Transferierbarkeit von Humankapital beim Arbeitsplatzwechsel. Einerseits werden zwei Maße entwickelt, die die Diskrepanz zwischen individueller Humankapitalstruktur und Anforderungen des Arbeitsplatzes im Falle eines Jobwechsels abbilden (human capital shortage und human capital redundancy). Andererseits werden bislang erworbene Qualifikationen als (auf den jeweiligen Arbeitsplatz bezogen) nützlich und nutzlos klassifiziert (useful skill experience und useless skill experience). Die dann folgende empirische Studie, welche die zuvor beschriebenen Maßzahlen nutzt, beruht auf demselben Datensatz, der auch in Kapitel zwei Verwendung findet.

Ein wesentliches Ergebnis der empirischen Analyse besteht darin, dass Individuen im Falle eines Arbeitsplatzwechsels bestrebt sind, den Verlust an Qualifikationen zu minimieren. Wechseln Individuen dennoch zu einer Beschäftigung, bei der ein nicht unwesentlicher Teil der zuvor erworbenen Qualifikationen brach liegt, werden selbige für die überflüssigen Qualifikationen nicht entgolten. Daraus folgt, dass die Opportunitätskosten eines solchen Jobwechsels proportional zum Maß der überflüssigen Qualifikationen steigen, da Letztere am alten Arbeitsplatz ja noch entgolten wurden. Des Weiteren zeigt sich, dass Individuen ebenfalls den Wechsel zu Arbeitsplätzen scheuen, die das Erlangen neuer Qualifikationen notwendig machen. Findet dennoch ein entsprechender Arbeitsplatzwechsel statt, so werden Individuen anfänglich für die fehlenden Qualifikationen gleichsam bestraft, indem sie sich Lohneinbußen gegenüber sehen. Allerdings ist später ein vergleichsweise starkes Lohnwachstum zu erkennen, das möglichweise darauf zurückzuführen ist, dass im Zeitablauf neu erworbene und für den Arbeitsplatz relevante Qualifikationen entsprechend entgolten werden. Darüber hinaus zeigt die Untersuchung, dass sich bisher angesammelte Qualifikationen in Berufen, die im Hinblick auf die Qualifikationsstruktur ähnlich dem jetzigen Beruf sind (verwandte Berufe), positiv auf den Lohnsatz auswirken.

Aus dem vierten Kapitel lassen sich zwei wesentliche Schlussfolgerungen für Forschung im Bereich Arbeit und Strukturwandel ableiten: zum einen weist Humankapital eine beträchtliche Breite auf, da es sich in hohem Maße zwischen verwandten Berufen transferieren lässt. Zum anderen können die Kosten des Strukturwandels beträchtlich sein, sofern aus selbigem die Obsoleszenz bestimmter Qualifikationen folgt. Je mehr Qualifikationen auf Arbeitnehmerebene, beispielsweise wegen neuer Technologien, überflüssig werden, desto höhere Lohneinbußen müssen die Individuen hinnehmen.

Das Schlusskapitel stellt eine kurze Zusammenfassung relevanter Erkenntnisse der vorherigen Kapitel dar und diskutiert sich daraus ergebene Möglichkeiten politischen Handelns. Darüber hinaus werden noch offene Forschungsfragen angerissen.

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Appendix A

Table A1: List and definitions of variables used in the factor analysis

Variable	Original question (wave 1979)	Scale
Strictly comparable questions to other waves		
Explicitness of tasks	Wie oft kommt es bei Ihrer täglichen Arbeit vor, dass Ihnen die Arbeitsdurchführung bis in alle Einzelheiten vorgeschrieben ist?	1-5
Repetitiveness of tasks	Wie oft kommt es bei Ihrer täglichen Arbeit vor, dass ein und derselbe Arbeitsgang sich bis in alle einzelheiten wiederholt?	1-5
Process improvement	Wie oft verlangt Ihre tägliche Arbeit bisherige Verfahren zu verbessern oder etwas neues auszuprobieren?	1-5
Arithmetic/math/statistics	Benötigen Sie: Rechnen, Mathematik, Statistik bei Ihrer beruflichen Tätigkeit?	dummy
Use of law	Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Gesetze/Recht anwenden und auslegen	dummy
Educate, teach	Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Erziehen, unterrichten, ausbilden, lehren	dummy
Comparable questions to other waves		
Research	Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Forschen, Auswerten, Erkunden?	dummy
Negotiate/consult	Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Mit Kunden/Anbietern verhandeln, Kunden beraten Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Verhandeln, Interessen Vertreten	dummy

Taking care of people	Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Betreuen, pflegen, versorgen	dummy
Medical care	Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Ärztlich untersuchen, diagnostizieren	dummy
Coordinate/organize	Tätigkeit die in der letzten Zeit bei Ihrer beruflichen Arbeit angefallen ist: Koordinieren, organizieren, disponieren	dummy
Markeing/sales	Benötigen Sie: Verkauf, Werbung, Marketing bei Ihrer beruflichen Tätigkeit?	dummy
Management	Benötigen Sie: Betriebsführung, Organization bei Ihrer beruflichen Tätigkeit?	dummy
Source: QCS, wave 1979		

Table A2: Occupational classification of the IABS

- Farmers till animal keepers and related occ. exc. land workers;
- Land workers;
- Gardeners, garden workers;
- Garden architects, garden managers till forest cultivators;
- Miners till Mineral preparers, mineral burners;
- Stone preparers till Shaped brick, concrete block makers;
- Ceramics workers till Glass processors, glass finishers;
- Chemical plant operatives+Chemical laboratory workers;
- Rubber makers, processors+Vulcanisers;
- Plastics processors;
- Paper, cellulose makers till Other paper products makers;
- Type setters, compositors till Printer's assistants;
- Iron, metal producers, melters till Metal drawers;
- Moulders, coremakers till Semi-finished product fettlers/other mould casting occ.;
- Sheet metal pressers, drawers, stampers till Other metal moulders;
- Turners;
- Drillers till Other metal-cutting occupations;
- Metal polishers till Enamellers, zinc platers and other metal surface finishers;
- Welders, oxy-acetylene cutters till Metal bonders and other metal connectors;
- Steel smiths till Pipe, tubing fitters exc. Plumbers;
- Plumbers;

- Locksmiths till Sheet metal, plastics fitters;
- Engine fitters;
- Plant fitters, maintenance fitters;
- Steel structure fitters, metal shipbuilders;
- Motor vehicle repairers;
- Agricultural machinery repairers till Precision mechanics;
- Other mechanics+Watch-, clockmakers;
- Toolmakers;
- Precision fitters till Doll makers, model makers, taxidermists;
- Electrical fitters, mechanics;
- Telecommunications mechanics, craftsmen;
- Electric motor, transformer fitters till Radio, sound equipment mechanics;
- Electrical appliance, electrical parts assemblers;
- Other assemblers;
- Metal workers (no further specification);
- Clothing sewers;
- Leather makers, catgut string makers till Skin processing operatives;
- Bakery goods makers+Confectioners (pastry);
- Butchers till Fish processing operatives;
- Cooks + Ready-to-serve meals, fruit, vegetable preservers, preparers;
- Wine coopers till Sugar, sweets, ice-cream makers;
- Bricklayers;
- Concrete workers;
- Carpenters+Scaffolders;
- Roofers;
- Paviors till Other civil engineering workers;
- Earth movers+Other building labourers, building assistants, n.e.c.;
- Stucco workers, plasterers, rough casters till Screed, terrazzo layers;
- Room equippers+Upholsterers, mattress makers;
- Carpenters till Other wood and sports equipment makers;
- Goods painters, lacquerers till Ceramics, glass painters;
- Goods examiners, sorters, n.e.c.;
- Packagers, goods receivers, despatchers;
- Assistants (no further specification);
- Generator machinists till Machine setters (no further specification);
- Mechanical, motor engineers;
- Electrical engineers;
- Architects, civil engineers;
- Survey engineers till Other manufacturing engineers;
- Other engineers;
- Chemists/chemical engineers/physicists/physics engineers/mathematicians/Building tech.;
- Mechanical engineering technicians;
- Electrical engineering technicians;
- Measurement technicians till Remaining manufacturing technicians;
- Other technicians;
- Foremen, master mechanics;
- Biological specialists till Photo laboratory assistants;
- Technical draughtspersons;
- Wholesale and retail trade buyers, buyers;
- Salespersons;
- Publishing house dealers, booksellers till Service-station attendants;

- Commercial agents, travellers+Mobile traders;
- Bank specialists+Building society specialists;
- Health insurance specialists+Life, property insurance specialists;
- Forwarding business dealers;
- Railway engine drivers, Street attendants;
- Railway controllers, conductors;
- Motor vehicle drivers;
- Navigating ships officers till Air transport occupations;
- Post masters till Telephonists exc. Postal deliverers;
- Postal deliverers;
- Warehouse managers, warehousemen;
- Transportation equipment drivers;
- Stowers, furniture packers+Stores, transport workers;
- Entrepreneurs, managing directors, divisional managers;
- Management consultants, organisors+Chartered accountants, tax advisers;
- Cost accountants, valuers;
- Accountants;
- Cashiers;
- Data processing specialists;
- Office specialists;
- Stenographers, shorthand-typists, typists;
- Office auxiliary workers;
- Factory guards, detectives till Judicial enforcers;
- Doormen, caretakers;
- Domestic and non-domestic servants;
- Journalists till Librarians, archivists, museum specialists;
- Musicians till Performers, professional sportsmen, auxiliary artistic occupations;
- Physicians till Pharmacists;
- Non-medical practitioners+Masseurs, physiotherapists and related occupations;
- Nurses, midwives;
- Nursing assistants;
- Dietary assistants, pharmaceutical assistants+Medical receptionists;
- Medical receptionists;
- Social workers, care workers+Work, vocational advisers;
- Home wardens, social work teachers;
- Uni teachers, lecturers at higher tech sch./academies/other teachers exc. Real-, Volks-, Sonder-.;
- Real-, Volks-, Sonder- school teach.;
- Economic and social scientists, statisticians till Religious care helpers;
- Hairdressers+Other body care occupations;
- Restaurant, inn, bar keepers, hotel proprietors, catering trade dealers;
- Waiters, stewards;
- Others attending on guests;
- Laundry workers, pressers+Textile cleaners, dyers and dry cleaners;
- Glass, buildings cleaners;
- Street cleaners, refuse disposers till Machinery, container cleaners and related.

We drop houseworkers, interns and volunteers and those that in the QCS have fewer than 10 observations or are not observed in all five waves

Table A3: Frequences of the QCS variables

1979		**1998/1999**		**2005/2006**	
Layoff risk					Percent
No risk	79.41	No risk	32.96	No risk	35
Low risk	17.55	Low risk	54.01	Low risk	55
High risk	3.04	High risk	8.79	High risk	6.83
		Very high risk	4.24	Very high risk	3.37
Total	100		100		100
Task explicitness					
0=sometimes;seldom;never	71.26	0=sometimes;seldom;never	66.04	0=sometimes;seldom;never	53.62
1=often; always	28.74	1=often; always	33.96	1=often	46.38
Total	100		100		100
Task repetitiveness					
0=sometimes;seldom;never	55.69	0=sometimes;seldom;never	52.23	0=sometimes;seldom;never	29.24
1=often; always	44.31	1=often; always	47.77	1=often	70.76
Total	100		100		100
Process improvement					
0=sometimes;seldom;never	79.53	0=sometimes;seldom;never	78.79	0=sometimes;seldom;never	25.66
1=often; always	20.47	1=often; always	21.21	1=often	74.34
Total	100		100		100
Educate, teach, lecture					
0=no	95.66	0=seldom, never	87.79	Never	48.38
1=yes	4.34	1=often	12.21	Sometimes	34.61
				Often	17.01
Total	100		100		100
Management knowledge					
0=no	79.87	0=no	86.48	0=no	79.55
1=yes	20.13	1=yes	13.52	1=yes	20.45
Total	100		100		100
Research, development, design					
0=no	97.61	0=seldom, never	95.52	0=never, sometimes	87.72
1=yes	2.39	1=often	4.48	1=often	12.28
Total	100		100		100
Law					
0=no	97.18	0=no	85.52	0=basic knowledge or less	81.11
1=yes	2.82	1=yes	14.48	1-specialized knowledge	18.89
Total	100		100		100
Medical or nursing knowledge					
0=no	96.15	0=no	89.76	0=basic knowledge or less	86.76

1=yes	3.85	1=yes	10.24	1-specialized knowledge	13.24
Total	100		100		100
Organize or coordinate					
0=no	82.83	0=seldom, never	67.75	0=never, sometimes	63.95
1=yes	17.17	1=often	32.25	1=often	36.05
Total	100		100		100
Mathematics, Statistics					
0=no	42.06	0=no	67.57	0=basic knowledge or less	72.29
1=yes	57.94	1=yes	32.43	1-specialized knowledge	27.71
Total	100		100		100
Marketing					
0=no	77.09	0=no	92.04	0=never, sometimes	86.33
1=yes	22.91	1=yes	7.96	1=often	13.67
Total	100		100		100
Sales /customer support					
0=no	82.11			0=never, sometimes	35.33
1=yes	17.89			1=often	64.67
Total	100		100		100
Gender					
0=male	67	0=male	57.64	0=male	53.87
1=female	33	1=female	42.36	1=female	46.13
Total	100		100		100
Education					
Unknown	16.22	Without degree	14.42	Without degree	8.87
Part-time vocational school	53.26	Part-time vocational school	66.66	Vocational traning	62
Full-time vocational school	9.64	Vocational training (Lehre)	9.58	Master/Technical school	7.45
Master/Technical school	6.36	Master/Technical school	3.96	University, polytechnic	21.59
Health school	1.52	University, polytechnic	5.38		
Civil servants school	2.97				
Other vocational school	2.73				
Berufsakademie/polytechnic	2.86				
University	2.56				
Other	1.88				
Total	100		100		100
Industry					
Agriculture, mining	3.97	Agriculture, mining	1.81	Agriculture, mining	2.12
Manufacturing	40.6	Manufacturing	35.72	Manufacturing	30.84
Construction	8.84	Construction	7.82	Construction	5.6

Railways, road transport	2.12	Railways, road transport	0.43	Railways, road transport	
Services	34.36	Services	44.09	Services	53.44
Public administration	7.7	Public administration	7.31	Public administration	4.78
Energy, garbage removal	1.21	Energy, garbage removal	1.44	Energy, garbage removal	1.63
Post	1.19	Post	1.39	Post	1.59
Total	100		100		100

Table A4: Correlations for Tables 2.6-2.8

1979

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Layoff risk	1															
(2) Task explicitness	0.10*	1														
(3) Task repetitiveness	0.08*	0.43*	1													
(4) Process improvement	-0.05*	-0.03*	-0.07*	1												
(5) Educate/teach	-0.05*	-0.05*	-0.06*	0.14*	1											
(6) Management	-0.10*	-0.13*	-0.12*	0.24*	0.15*	1										
(7) Research	-0.03*	-0.03*	-0.04*	0.14*	0.11*	0.08*	1									
(8) Use of law	-0.04*	-0.03*	-0.06*	0.04*	0.15*	0.10*	0.09*	1								
(9) Medical/cosmetic care	-0.04*	-0.02*	0.00	0.06*	0.14*	0.01*	0.02*	-0.02*	1							
(10) Organize/coordinate	-0.10*	-0.12*	-0.14*	0.20*	0.26*	0.40*	0.14*	0.17*	0.02*	1						
(11) Arithm./math/stats	-0.09*	-0.13*	-0.12*	0.12*	0.07*	0.26*	0.08*	0.07*	-0.07*	0.22*	1					
(12) Marketing	-0.05*	-0.17*	-0.09*	0.14*	0.04*	0.35*	0.03*	-0.02*	-0.03*	0.18*	0.27*	1				
(13) Sales/customer care	-0.04*	-0.16*	-0.08*	0.08*	0.05*	0.20*	0.04*	0.00	-0.02*	0.16*	0.21*	0.56*	1			
(14) Gender (1=female)	0.01	-0.01	0.10*	-0.11*	0.00	-0.10*	-0.04*	-0.07*	0.17*	-0.16*	-0.04*	0.06*	0.10*	1		
(15) Age	-0.08*	-0.01	0.01	-0.01	0.01	0.07*	-0.02*	0.00	-0.09*	0.09*	-0.03*	-0.02*	-0.02*	-0.14*	1	
(16) Education	-0.05*	-0.05*	-0.06*	0.14*	1.00*	0.15*	0.11*	0.15*	0.14*	0.26*	0.07*	0.04*	0.05*	0.00	0.01	1

*Significant at 5% or better; Source: QCS

Table A4, continued

1998/1999

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Layoff risk	1.00															
(2) Task explicitness	0.13*	1.00														
(3) Task repetitiveness	0.06*	0.48*	1.00													
(4) Process improvement	-0.05*	-0.06*	-0.09*	1.00												
(5) Educate/teach	-0.10*	-0.08*	-0.08*	0.17*	1.00											
(6) Management	-0.10*	-0.14*	-0.14*	0.21*	0.23*	1.00										
(7) Research	0.00	-0.07*	-0.10*	0.26*	0.07*	0.11*	1.00									
(8) Use of law	-0.10*	-0.07*	-0.09*	0.14*	0.17*	0.34*	0.02*	1.00								
(9) Medical/cosmetic care	-0.04*	0.00	0.01	0.05*	0.12*	0.06*	0.00	0.06*	1.00							
(10) Organize/coordinate	-0.12*	-0.19*	-0.18*	0.28*	0.26*	0.42*	0.16*	0.25*	0.07*	1.00						
(11) Arithm./math/stats	-0.06*	-0.09*	-0.10*	0.15*	0.07*	0.18*	0.11*	0.21*	-0.08*	0.20*	1.00					
(12) Marketing	-0.04*	-0.10*	-0.10*	0.10*	0.06*	0.31*	0.03*	0.17*	-0.04*	0.25*	0.15*	1.00				
(13) Sales/customer care	-0.13*	-0.21*	-0.15*	0.19*	0.25*	0.27*	0.09*	0.21*	0.11*	0.38*	0.16*	0.22*	1.00			
(14) Gender (1=female)	-0.04*	-0.02*	0.08*	-0.12*	-0.06*	-0.08*	-0.10*	-0.02*	0.22*	-0.06*	-0.10*	-0.04*	0.11*	1.00		
(15) Age	-0.11*	-0.05*	0.00	0.00	0.03*	0.08*	0.00	0.06*	-0.04*	0.06*	0.00	0.02*	0.02*	-0.04*	1.00	
(16) Education	-0.10*	-0.08*	-0.08*	0.17*	1.00*	0.23*	0.07*	0.17*	0.12*	0.26*	0.07*	0.06*	0.25*	-0.06*	0.03*	1.00

*Significant at 5% or better; Source: QCS

Table A4, continued.

2005/2006																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Layoff risk	1.00															
(2) Task explicitness	0.07*	1.00														
(3) Task repetitiveness	0.01	0.30*	1.00													
(4) Process improvement	-0.03*	-0.05*	-0.11*	1.00												
(5) Educate/teach	-0.03*	-0.04*	-0.07*	0.21*	1.00											
(6) Management	-0.02*	-0.10*	-0.07*	0.11*	0.13*	1.00										
(7) Research	0.01	-0.11*	-0.18*	0.16*	0.11*	0.02	1.00									
(8) Use of law	-0.02*	-0.02*	-0.05*	0.09*	0.16*	0.21*	0.01	1.00								
(9) Medical/cosmetic care	0.00	0.03*	0.02*	0.08*	0.21*	-0.09*	-0.01	0.14*	1.00							
(10) Organize/coordinate	-0.04*	-0.07*	-0.07*	0.19*	0.27*	0.15*	0.14*	0.10*	0.10*	1.00						
(11) Arithm./math/stats	0.00	-0.05*	-0.09*	0.13*	0.13*	0.22*	0.21*	0.13*	-0.10*	0.11*	1.00					
(12) Marketing	0.00	-0.08*	-0.07*	0.10*	0.10*	0.19*	0.06*	0.07*	0.01	0.14*	0.01	1.00				
(13) Sales/customer care	-0.04*	-0.10*	-0.10*	0.18*	0.26*	0.22*	0.09*	0.18*	0.15*	0.24*	0.07*	0.22*	1.00			
(14) Gender (1=female)	-0.02	0.03*	0.14*	-0.06*	-0.05*	-0.03*	-0.14*	0.03*	0.22*	-0.05*	-0.19*	0.02*	0.08*	1.00		
(15) Age	-0.05*	-0.07*	-0.01	-0.02	-0.03*	0.00	-0.01	0.02*	-0.01	0.00	0.01	0.01	0.00	0.00	1.00	
(16) Education	0.02*	-0.17*	-0.27*	0.18*	0.16*	0.20*	0.24*	0.15*	0.05*	0.14*	0.17*	0.11*	0.19*	-0.13*	0.08*	1.00
*Significant at 5% or better; Source: QCS																

Factor Analysis

The basic idea behind the use of factor analysis (FA) is that the multiple tasks that enter our empirical design can actually be reduced to few dimensions that give us almost the same information as the full set of variables. The resulting factors from FA are orthogonal by construction which is a very favorable feature in multiple regression. The FA can also be confirmatory to the belief that there exist abstract, interactive and codifiable dimensions.

Formally, FA assumes that L characteristic tasks of occupations can be represented by K task dimensions, where $K < L$ without much loss of information. The identification of these underlying dimensions (factors) can be represented with the following set of linear models:

(1) $C_{ij} = \lambda_{i1}\theta_{ij} + \lambda_{i2}\theta_{2j} + ... + \lambda_{ik}\theta_{kj} + \varepsilon_{ij}$

where $i = 1, ..., l$ and $C_{ij}$is the intensity of task i for occupation j. $\theta_{kj}$is the amount of the underlying task k present in occupation j, $\lambda_{ik}$is the factor loading of task j on task dimension k and $\varepsilon_{ij}$is an independently distributed error term which may differ in each equation. In this set of models only C_{ij} are known to us. As evident from the formulation, FA posits that C_{ij} are a linear combination of k unobserved factors indicated with the letter θ in the above equations. The intercepts of the equations are by construction equal to zero[5].

The above set of models can be represented in a matrix form:

(2) $\mathbf{c_j} = \mathbf{\Lambda}\boldsymbol{\theta}_\mathbf{j} + \boldsymbol{\varepsilon}_\mathbf{j}$,

where $\mathbf{c_j}$ is l by 1 vector of observed variables, $\mathbf{\Lambda}$ is an l by k matrix of factor loadings, $\boldsymbol{\theta_j}$is a k by 1 vector of underlying factors, and $\boldsymbol{\varepsilon_j}$is a l by 1 vector of measurement errors. We can stack equation (2) over occupations and drop the index $\boldsymbol{j}$ which yields:

(3) $\boldsymbol{C} = \mathbf{\Theta\Lambda'} + \boldsymbol{E}$,

[5]On one hand the intercepts are of no interest for the FA purpose, on the other it is not possible to estimate both the factor loading and the intercept simultaneously (e.g., Bollen 1989).

where now $\boldsymbol{C}$ is a n by l matrix of observed variable values, $\boldsymbol{\Theta}$is an n by k matrix of scores of the underlying factors, $\boldsymbol{\Lambda'}$is the transpose of an l by k matrix of factor loadings and $\boldsymbol{E}$ is an n by l matrix of measurement errors.

The only input that enters the factor analysis is the matrix $\boldsymbol{C}$. In fact, all the information necessary for the estimation of $\boldsymbol{\Theta}$and$\boldsymbol{\Lambda}$is the covariance matrix of the observable variables. In order to identify these matrices we need certain assumptions:

(4a) $E(\boldsymbol{E'\Theta}) = E(\boldsymbol{\Theta' E}) = 0$

(4b) $E(\boldsymbol{E'E}) = \boldsymbol{\Delta_e}$

(4c) $E(\boldsymbol{\Theta'\Theta}) = \boldsymbol{\Phi}$

(4d) $E(\boldsymbol{C'C}) = \boldsymbol{\Sigma}$,

where $\boldsymbol{\Phi}$ is a k by k variance-covariance matrix of the underlying factors, $\boldsymbol{\Sigma}$ represents the l by l variance-covariance matrix of the data and $\boldsymbol{\Delta_e}$is an l by l variance-covariance matrix of the errors. Under these assumptions we can rewrite (3) as:

(5) $\boldsymbol{\Sigma = \Lambda\Phi\Lambda' + \Delta_e}$

This means that the variances and the covariances among the observed variables can be decomposed into a component attributable to the underlying factors and a component attributable to the variaces and covariances of the measurement errors. Because the number of unique elements in (5) $l(l+1)/2$ is still larger than the number of elements that need to be estimated $lk + k(k+1)/2 + l(l+1)/2$, two further constraints need to be made in order to make (5) identifiable. One constraint is that $\boldsymbol{\Phi}$ is identity matrix (which results in factors that are orthogonal among each other and with variance 1). The second one is that $\boldsymbol{\Delta_e}$must to be diagonal.

The 14 variables resulted in three factors that had eigenvalues above one. The eigenvalues measure the variance in all variables that is accounted by a factor. As a rule of thumb factors with eigenvalues of at least one are considered to explain non-trivial amount of the total variance in the data. In the 1979 wave these three factors have eigenvalues of 5.4, 1.75 and 1.27 and together explain 94% of the total variance in the 14 variables. Based on the factor loadings on different variables and the occupational rankings on each of these factors we interpret the first one as abstract dimension, the second one as sales dimension and the third one as the care dimension. Table A5 presents the factor loadings.

Table A5: Factor loadings

Variable	Abstract skills	Sales-related	Care-related
Reseach	0.74		
Negotiate/consult		0.94	
Use of law	0.49		
Taking care of people			0.78
Medical/cosmetic care			0.75
Negotiate/represent	0.58	0.59	
Organize/coordinate	0.91		
Process improvement	0.73		
Explicitness of tasks	-0.43	-0.47	-0.31
Repetitiveness of tasks	-0.68		
Arithmetic/math/stats	0.65	0.38	
Marketing/sales		0.96	
Management	0.79	0.44	

Source: QCS, 1979 wave. N=115. Results of a factor analysis after rotation. Only loading of .3 or higher are displayed.

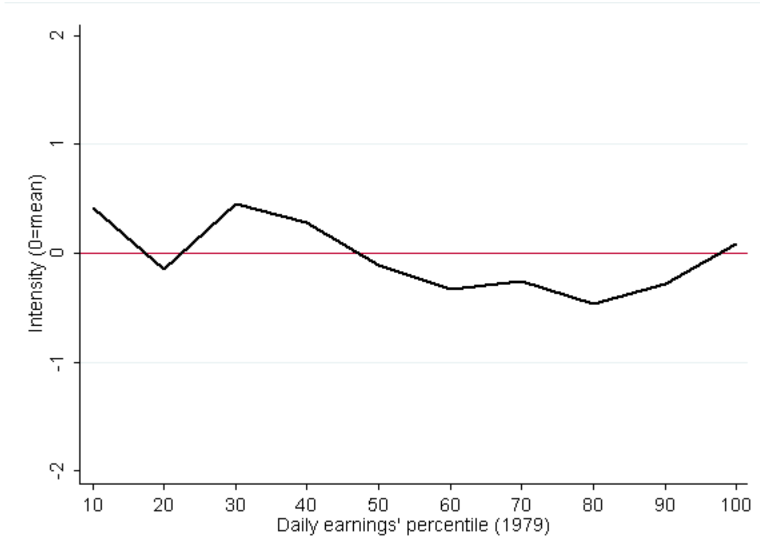

Figure A1: Care-for-others intensity along the wage distribution

Source: IABS Regional and QCS, 1979. Note: Care-for-others is a factor from a factor analysis. It has a mean of zero and a S.D. of one.

Appendix B

Table B1: List and definitions of variables used in the factor analysis

Variable	Original question (wave 1998/1999)	Scale
	Strictly comparable questions	
Explicitness of tasks	Wie häufig kommt es bei Ihrer täglichen Arbeit vor, dass Ihnen die Arbeitsdurchführung bis in alle Einzelheiten vorgeschrieben ist?	1-5
Repetitiveness of tasks	Wie häufig kommt es bei Ihrer täglichen Arbeit vor, dass ein und derselbe Arbeitsgang sich bis in alle einzelheiten wiederholt?	1-5
Process improvement	Wie häufig kommt es bei Ihrer Arbeit vor, dass Sie bisherige Verfahren verbessern oder etwas neues auszuprobieren?	1-5
Arithmetic/ math/ statistics	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Kentnisse, also nicht nur Grundkentnisse in der Gebiet: Rechnen, Mathematik, Statistik?	dummy
Use of law	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Kentnisse, also nicht nur Grundkentnisse in der Gebiet: Arbeitsrecht, Betriebsverfassungsgesetz, Tarifrecht, Kündigungsschutz oder andere Rechtskentnisse?	dummy
Educate/teach	Wie haüfig kommt bei Ihrer Arbeit vor: Ausbilden, Lehren, Unterrichten?	1-3
	Comparable questions	
Research	Wie haüfig kommt bei Ihrer Arbeit vor: Entwickeln, Forschen?	1-3
Negotiate/ consult	Wie haüfig kommt bei Ihrer Arbeit vor: Verhandlunge führen?	1-3
Taking care of people	Wie haüfig kommt bei Ihrer Arbeit vor: Versorgen, Bedienen, Betreuen von Menschen?	1-3
Medical knowledge	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Medizinische Kentnisse, also nicht nur Grundkentnisse?	dummy
Organize/ coordinate	Wie haüfig kommt bei Ihrer Arbeit vor: Organizieren, Planen?	1-3
Markeing/ sales	Wie haüfig kommt bei Ihrer Arbeit vor: Werben, PR, Marketing, Akquirieren?	1-3
Management	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Kentnisse, also nicht nur Grundkentnisse in der Gebiet: Management, Personalführung, Organisation, Planung?	dummy
Source: QCS, wave 1998/1999		

Table B2: Descriptive statistics

	Mean	Median	Std. dev.	Min	Max	Obs.
Construction						
Cost share of abstract labor	0.37	0.37	0.13	0.05	0.87	1727
Cost share of codifiable labor	0.46	0.47	0.15	0.05	0.84	1727
Cost share of interactive labor	0.17	0.16	0.07	0.05	0.48	1727
P_A/P_I	2.43	2.08	1.43	0.23	17.00	1727
P_C/P_I	3.25	3.00	1.92	0.41	12.02	1727
Employment abstract	24.38	7.11	67.46	0.02	995.45	1727
Employment codifiable	29.18	9.19	66.95	0.21	1,116.05	1727
Employment interactive	15.82	4.51	44.42	0.12	738.18	1727
Plant-level wage bill (abstract)	419.81	71.08	1,358.83	1.06	20,306.93	1727
Plant-level wage bill (codifiable)	403.6	105.99	920.27	1.43	12,816.63	1727
Plant-level wage bill (interactive)	138.51	36.17	390.04	1.17	6,488.72	1727
Average daily wage (abstract)	7.35	7.09	3.54	1.43	20.79	1727
Average daily wage (codifiable)	5.8	4.98	3.35	1.05	37.5	1727
Average daily wage (interactive)	2.51	2.38	0.74	1.17	6.43	1727
Variable costs (daily)	961.92	229.21	2,533.88	4.94	34,790.64	1727
Deflated sales (€1000)	6,949.11	1,223.75	24,300	12.73	431,000	1727
Non-IT capital (€1000)	756.15	85.11	3,952.13	0.004	74,100	1727
IT capital (€1000)	42.81	4.87	198.34	0.002	3,037.98	1727
Outsourced parts	0.01	0	0.11	0	1	1727
Retail						
Cost share of abstract labor	0.38	0.34	0.12	0.13	0.90	812
Cost share of codifiable labor	0.21	0.19	0.08	0.04	0.63	812
Cost share of interactive labor	0.42	0.46	0.11	0.06	0.62	812
P_A/P_I	1.18	0.76	1.36	0.29	15.27	812
P_C/P_I	0.58	0.44	0.46	0.19	5.38	812
Employment abstract	46.82	11.38	111.89	0.51	1,041.48	812
Employment codifiable	30.11	6.52	69.82	0.02	597.69	812
Employment interactive	65.03	12.7	160.08	0.18	1,443.43	812
Plant-level wage bill (abstract)	404.75	86.49	943.17	1.65	8,686.11	812
Plant-level wage bill (codifiable)	227.3	49.95	524.39	1.07	4,599.84	812
Plant-level wage bill (interactive)	528.33	85.99	1358.34	1.55	12,890.73	812
Average daily wage (abstract)	2.66	2.29	1.36	1.07	12.98	812
Average daily wage (codifiable)	5	4.26	3.38	1.58	40.67	812
Average daily wage (interactive)	5.16	5.29	1.41	1.55	9.75	812
Variable costs (daily)	1,160.38	241.86	2802	5.33	26,176.68	812

Deflated sales (€1000)	15,300	3,017.04	32,400	17.22	273,000	812
Non-IT capital (€1000)	1,294.07	79.13	6,537.04	0.004	74,900	812
IT capital (€1000)	69.07	9.92	207.58	0.002	2,379.46	812
Outsourced parts	0.02	0	0.14	0	1	812

	Mean	Median	Std. dev.	Min	Max	Obs.
Wholesale						
Cost share of abstract labor	0.48	0.46	0.17	0.12	0.94	657
Cost share of codifiable labor	0.23	0.20	0.11	0.02	0.61	657
Cost share of interactive labor	0.30	0.32	0.10	0.04	0.50	657
P_A/P_I	2.16	1.44	2.12	0.25	22.66	657
P_C/P_I	0.82	0.67	0.56	0.18	5.12	657
Employment interactive	53	16	101.23	0.31	714	657
Employment codifiable	35	10	64.34	0.07	424	657
Employment abstract	58	17	135.56	0.45	1,178	657
Plant-level wage bill (abstract)	1,026	194	3066.6	2.62	31096.17	657
Plant-level wage bill (codifiable)	334	91	646.96	1.13	4,771	657
Plant-level wage bill (interactive)	471	139	939.71	2.09	6,841	657
Average daily wage (abstract)	3.61	3.02	1.82	1.13	13.35	657
Average daily wage (codifiable)	9.07	6.76	7.56	1.35	107.35	657
Average daily wage (interactive)	4.69	4.74	1.07	2.09	8.79	657
Variable costs (daily)	1,831.20	472.99	4329.84	6.29	39,168.26	657
Deflated sales (€1000)	80,200	9,723.20	388,000	56.64	5,300,000	657
Non-IT capital (€1000)	1,924.39	250.24	10,700	0.004	182,000	657
IT capital (€1000)	338.98	29.58	1,344.61	0.002	14,800	657
Outsourced parts	0.02	0	0.15	0	1	657
Metal production						
Cost share of abstract labor	0.34	0.32	0.13	0.05	0.72	844
Cost share of codifiable labor	0.46	0.45	0.14	0.13	0.89	844
Cost share of interactive labor	0.20	0.19	0.06	0.06	0.49	844
P_A/P_I	1.87	1.62	1.01	0.43	6.60	844
P_C/P_I	2.68	2.16	1.66	0.38	14.90	844
Employment abstract	66.66	18.1	134.73	0.04	1,304.19	844
Employment codifiable	96.98	33.89	178.75	0.34	1,346.64	844
Employment interactive	65.22	19.78	127.17	0.27	1,256.22	844
Plant-level wage bill (abstract)	1,387.07	287.82	3,030.01	1.13	27,488.75	844
Plant-level wage bill (codifiable)	1,574.55	448.77	3,276.35	2.05	27,961.38	844
Plant-level wage bill (interactive)	591.76	166.65	1,183.75	2.12	11,515.48	844

Average daily wage (abstract)	8.37	7.29	3.88	2.05	29.83	844
Average daily wage (codifiable)	6.16	5.42	3.42	1.13	23.04	844
Average daily wage (interactive)	3.3	3.25	0.61	1.58	6.48	844
Variable costs (daily)	3,553	1,034	7,175.80	7.25	57503.43	844
Deflated sales (€1000)	23,300	5,176.75	52,300	55.8	473,000	844
Non-IT capital (€1000)	3,612.68	458.44	10,100	0.004	129,000	844
IT capital (€1000)	266.57	29.15	919.99	0.002	15,700	844
Outsourced parts	0.02	0	0.14	0	1	844

	Mean	Median	Std. dev.	Min	Max	Obs.
General and special purpose technology						
Cost share of abstract labor	0.45	0.45	0.17	0.06	0.91	940
Cost share of codifiable labor	0.37	0.36	0.15	0.04	0.81	940
Cost share of interactive labor	0.18	0.17	0.07	0.05	0.43	940
P_A/P_I	3.10	2.51	2.41	0.26	19.13	940
P_C/P_I	2.27	1.95	1.38	0.24	11.66	940
Employment abstract	139.18	35.2	253.14	0.02	3020.93	940
Employment codifiable	171.6	42.1	329.95	0.28	2654.63	940
Employment interactive	124.52	27.75	250.7	0.3	2107.9	940
Plant-level wage bill (abstract)	4034.95	690.27	10,097.55	1.07	124741.8	940
Plant-level wage bill (codifiable)	2705.15	598.34	5,430.93	2.87	42851.11	940
Plant-level wage bill (interactive)	1189.1	238.88	2,421.27	2.21	22650.37	940
Average daily wage (abstract)	7.34	6.4	3.34	1.57	22.22	940
Average daily wage (codifiable)	10.26	8.59	8.68	1.07	55.4	940
Average daily wage (interactive)	3.41	3.41	0.64	1.41	7.78	940
Variable costs (daily)	7929.19	1649.21	16,427.17	10.76	190,243.30	940
Deflated sales (€1000)	61,600	7,832	134	97.5	1,020,000	940
Non-IT capital (€1000)	5,683.12	1,014.59	11,500	0.004	84,700	940
IT capital (€1000)	467.39	86,73	1,162.58	0.002	15,600	940
Outsourced parts	0.02	0	0.14	0	1	940
Control, optical instruments and watches						
Cost share of abstract labor	0.43	0.37	0.17	0.13	0.86	333
Cost share of codifiable labor	0.26	0.21	0.13	0.06	0.67	333
Cost share of interactive labor	0.31	0.31	0.15	0.06	0.51	333
P_A/P_I	2.42	1.17	2.76	0.52	14.39	333
P_C/P_I	1.23	0.75	1.11	0.33	7.10	333
Employment abstract	76.09	12.04	183.92	0.36	1020.98	333
Employment codifiable	69.43	8.33	160.25	0.44	686.09	333

Employment interactive	53.98	12.21	115.43	0.4	557.22	333
Plant-level wage bill (abstract)	2549.89	86.84	8,029.81	2.18	59998.65	333
Plant-level wage bill (codifiable)	975.69	53.62	2,441.05	1.94	13010.6	333
Plant-level wage bill (interactive)	488.58	85.22	1,100.91	2.38	5368.61	333
Average daily wage (abstract)	4.27	2.9	2.84	1.54	12.78	333
Average daily wage (codifiable)	8.45	4.81	8.34	1.95	46.55	333
Average daily wage (interactive)	4.14	4.1	1.07	1.8	6.4	333
Variable costs (daily)	4014.15	235.83	10,862.40	7.54	69673.49	333
Deflated sales (€1000)	29,200	1,026	99,800	39.56	940,000	333
Non-IT capital (€1000)	4,221.91	85.95	14,700	0.004	137,000	333
IT capital (€1000)	452,.51	11.75	2,225.58	0.002	22,300	333
Outsourced parts	0.02	0	0.15	0	1	333

	Mean	Median	Std. dev.	Min	Max	Obs.
Motor vehicles manufacturing						
Cost share of abstract labor	0.37	0.37	0.15	0.07	0.79	377
Cost share of codifiable labor	0.43	0.44	0.17	0.12	0.82	377
Cost share of interactive labor	0.20	0.18	0.08	0.06	0.44	377
P_A/P_I	2.19	1.83	1.35	0.32	9.06	377
P_C/P_I	2.80	1.97	1.98	0.40	12.03	377
Employment abstract	373.76	33.69	1,253.92	0.31	9209.84	377
Employment codifiable	592.66	51.24	1,637.74	0.31	10173.14	377
Employment interactive	380.95	36.88	1,190.34	0.21	8061.11	377
Plant-level wage bill (abstract)	13106.3	478.43	51,464.06	1.98	418190	377
Plant-level wage bill (codifiable)	11818.1	706.3	31,582.52	1.61	197324.8	377
Plant-level wage bill (interactive)	3812.71	316.75	12,240.12	1.3	81735.96	377
Average daily wage (abstract)	9.04	7.07	5.68	1.61	23.4	377
Average daily wage (codifiable)	7.38	6.09	4.81	1.35	31.49	377
Average daily wage (interactive)	3.41	3.34	0.76	1.3	6.03	377
Variable costs (daily)	28737.1	1562.72	91,045.35	5.39	646867.5	377
Deflated sales (€1000)	241,000	10,800	867,000	58.56	9,780,000	377
Non-IT capital (€1000)	36,600	1,100.04	146,000	0.004	1,590,000	377
IT capital (€1000)	1,452.78	69.46	5,121.34	0.002	50,000	377
Outsourced parts	0.04	0	0.18	0	1	377
Chemicals and pharma						
Cost share of abstract labor	0.46	0.47	0.14	0.12	0.95	382
Cost share of codifiable labor	0.34	0.34	0.12	0.03	0.65	382
Cost share of interactive labor	0.20	0.18	0.06	0.02	0.47	382

P_A/P_I	2.70	2.44	2.31	0.45	40.88	382
P_C/P_I	1.81	1.88	0.62	0.44	4.88	382
Employment abstract	223.33	51.9	578.74	0.17	4522.25	382
Employment codifiable	226.91	63.64	421.71	0.17	2348.53	382
Employment interactive	187.73	50.4	401.73	0.08	2790.07	382
Plant-level wage bill (abstract)	5357.99	1171.78	16,850.15	1.53	139218.9	382
Plant-level wage bill (codifiable)	2820.9	764.73	5,298.51	2.58	29127.45	382
Plant-level wage bill (interactive)	1669.24	407.37	3,779.45	2.35	27311.94	382
Average daily wage (abstract)	6.55	6.83	2.03	1.38	13.3	382
Average daily wage (codifiable)	9.6	8.99	9.6	1.53	48.09	382
Average daily wage (interactive)	3.71	3.73	3.71	1.18	5.44	382
Variable costs (daily)	9848.13	2350.43	24,897.14	11.51	193829.3	382
Deflated sales (€1000)	116,000	21,400	330,000	24.04	2,740,000	382
Non-IT capital (€1000)	22,200	2,995.81	55,300	0.004	395,000	382
IT capital (€1000)	996.47	124.27	3,030.30	0.002	36,300	382
Outsourced parts	0.04	0	0.19	0	1	382

	Mean	Median	Std. dev.	Min	Max	Obs.
Plastics and rubber						
Cost share of abstract labor	0.29	0.26	0.13	0.06	0.73	384
Cost share of codifiable labor	0.53	0.52	0.16	0.10	0.86	384
Cost share of interactive labor	0.18	0.16	0.09	0.06	0.56	384
P_A/P_I	1.89	1.73	1.04	0.24	6.42	384
P_C/P_I	3.99	2.72	2.78	0.46	15.06	384
Employment abstract	53.04	25.71	72.38	0.23	600.26	384
Employment codifiable	103.19	52.5	166.67	0.68	1513.45	384
Employment interactive	54.63	23.57	112.33	0.33	1188.74	384
Plant-level wage bill (abstract)	1010.36	362.56	1,799.25	4.12	18745.05	384
Plant-level wage bill (codifiable)	1972.88	665.75	3,516.49	2.78	26073.51	384
Plant-level wage bill (interactive)	531.82	213.15	1,119.37	3.51	12054.63	384
Average daily wage (abstract)	10.52	9.31	5.12	1.39	25.41	384
Average daily wage (codifiable)	5.48	4.99	3.05	0.99	19.37	384
Average daily wage (interactive)	3.16	2.89	1.12	1.29	8.27	384
Variable costs (daily)	3515.06	1412.36	5,978.99	10.42	52633.7	384
Deflated sales (€1000)	25,900	7,486.20	47,800	37.05	460,000	384
Non-IT capital (€1000)	4,620.15	1,093.69	10,300	0.004	126,000	384
IT capital (€1000)	176.96	39.85	341.99	0.002	3,281.42	384
Outsourced parts	0.04	0	0.18	0	1	384

Glass, bricks, and ceramics						
Cost share of abstract labor	0.33	0.31	0.12	0.08	0.79	349
Cost share of codifiable labor	0.42	0.42	0.12	0.09	0.79	349
Cost share of interactive labor	0.24	0.24	0.07	0.07	0.40	349
PA/PI	1.55	1.33	0.95	0.52	7.02	349
PC/PI	1.99	1.73	1.38	0.48	10.00	349
Employment abstract	48.64	18.78	72.24	0.34	423.92	349
Employment codifiable	77.84	29.12	113.7	0.34	666.34	349
Employment interactive	56.31	23.01	78.17	0.58	383.64	349
Plant-level wage bill (abstract)	750.51	250.88	1,220.24	2.53	6044.29	349
Plant-level wage bill (codifiable)	952.89	298.88	1,397.77	2.02	7886.96	349
Plant-level wage bill (interactive)	474.15	179.57	668.56	3.33	3259.98	349
Average daily wage (abstract)	6.83	6.49	2.69	1.9	18.9	349
Average daily wage (codifiable)	5.65	4.85	3.34	1.24	26.09	349
Average daily wage (interactive)	3.76	3.73	0.76	1.49	6.65	349
Variable costs (daily)	2177.54	775.49	3,177.04	10.05	16130.42	349
Deflated sales (€1000)	17,200	6,857.04	25,900	40.51	142,000	349
Non-IT capital (€1000)	2,556.02	697.11	4,486.09	0.004	24,200	349
IT capital (€1000)	158.58	20.72	331.24	0.002	1,836.40	349
Outsourced parts	0.02	0	0.13	0	1	349

	Mean	Median	Std. dev.	Min	Max	Obs.
Iron and steel						
Cost share of abstract labor	0.30	0.28	0.12	0.05	0.62	394
Cost share of codifiable labor	0.52	0.50	0.15	0.16	0.88	394
Cost share of interactive labor	0.18	0.17	0.07	0.07	0.40	394
PA/PI	1.79	1.68	0.86	0.48	6.04	394
PC/PI	3.62	2.68	2.37	0.53	13.17	394
Employment abstract	157.5	34.36	157.5	0.13	2307.28	394
Employment codifiable	246.58	67.22	499.91	0.34	3329.61	394
Employment interactive	168.02	37.17	369.53	0.28	2379.22	394
Plant-level wage bill (abstract)	3177.75	563.22	7,216.41	2.37	44736.92	394
Plant-level wage bill (codifiable)	4300.08	1292.6	8,158.86	2.06	48199.85	394
Plant-level wage bill (interactive)	1607.87	343.72	3,535.52	2.87	22213.24	394
Average daily wage (abstract)	11.01	10	5.25	2.06	26.23	394
Average daily wage (codifiable)	6.01	5.51	3	1.18	16.67	394
Average daily wage (interactive)	3.38	3.28	0.79	1.44	5.26	394
Variable costs (daily)	9085.7	2336.06	18,415.51	10.36	115068.3	394
Deflated sales (€1000)	90,400	11,300	255,000	97.19	2,270,000	394
Non-IT capital (€1000)	15,800	1,634.43	39,000	0.004	271,000	394

IT capital (€1000)	911.35	86.94	3,370.19	0.002	40,200	394
Outsourced parts	0.02	0	0.15	0	1	394
Electrical equipment						
Cost share of abstract labor	0.46	0.50	0.19	0.09	0.94	314
Cost share of codifiable labor	0.34	0.29	0.17	0.03	0.80	314
Cost share of interactive labor	0.20	0.19	0.07	0.03	0.36	314
P_A/P_I	3.04	2.26	3.66	0.39	27.83	314
P_C/P_I	1.85	1.50	1.29	0.45	7.15	314
Employment abstract	94.72	44.5	123.84	0.67	672.32	314
Employment codifiable	141.61	47.07	213.61	0.28	1541.67	314
Employment interactive	107.14	34.09	149.45	0.23	858.45	314
Plant-level wage bill (abstract)	2476.13	755.21	3,800.36	4.93	21343.48	314
Plant-level wage bill (codifiable)	1974.82	615.7	3,857.46	2.35	34016.91	314
Plant-level wage bill (interactive)	923.42	270.03	1,323.70	2.1	8137.16	314
Average daily wage (abstract)	6.39	5.53	3.7	1.34	16.15	314
Average daily wage (codifiable)	9.98	7.62	8.91	1.28	62.18	314
Average daily wage (interactive)	3.57	3.66	0.81	1.82	5.41	314
Variable costs (daily)	5374.37	1904.16	8,248.17	10.98	58205.28	314
Deflated sales (€1000)	53,600	15,300	101,000	100	570,000	314
Non-IT capital (€1000)	9,030.69	1,571.51	17,600	0.004	99,200	314
IT capital (€1000)	613.1	57.07	1,818.84	0.002	19,600	314
Outsourced parts	0.02	0	0.15	0	1	314

Measurement of capital stocks

We use investment expenditure data reported in the Linked Employer-Employee Panel (LIAB) to approximate stocks of IT and non-IT capital. Working with measures of capital stock rather than with capital flows has the virtue one does not need to rely on the assumption of proportionality of (replacement) investments and capital stock, which is difficult to test empirically. Moreover, in our approach so far missing values and zero investments lead to implausibly high variations in the (by assumption) proportional capital data series, probably causing measurement errors and an attenuation bias (Mueller 2008). Constructing capital stocks will alleviate these problems. The most commonly employed approach in capital stock measurement is the Perpetual Inventory Method (PIM). This method bases on constant exponential decay of capital goods (geometric deterioration), implying that capital services never actually reach zero and every unit of investment is perpetually part of the capital stock[6]. With a given constant rate of depreciation $\delta_i$that is constant over time, but different for each asset type i, the PIM essentially assumes that $K_{i,t} = K_{i,t-1}(1 - \delta_i) + I_{i,t}$, where $K_{i,t}$ is the capital stock (for a particular asset type i) at the end of period t, and $I_{i,t}$ denotes the investments in asset type i in period t. For the practical implementation of PIM we divide capital inputs into two asset types, namely IT and non-IT capital. We derive depreciation rates by industry from the EU KLEMS database as described in O'Mahony and Timmer (2009)[7]. There are several advantages of using the depreciation rates provided by EU KLEMS (Timmer et al. 2007). First, the rates are based on empirical research, rather than ad-hoc assumptions based on e.g., tax laws. Second, the EU KLEMS depreciation rates are available by industry and have much more asset detail than the investment series published by the German Statistical Office. Specifically, it turned out that the components of IT in EU KLEMS closely match the definition of IT employed in the

[6]Hulten and Wykoff (1981) tested several standard assumptions regarding depreciation rates and found that constant exponential depreciation performed reasonably well in describing exhibited data patterns.

[7]In fact, depreciation rates used in the EU KLEMS database are obtained from the U.S. Bureau of Economic Analysis (BEA). See Fraumeni (1997) for details.

LIAB data. Third and finally, since in particular IT assets are subject to rapid technological change and improvements in quality, hedonic price measurement is adopted in the calculation of EU KLEMS depreciation rates to adjust for quality. Altogether, EU KLEMS provides depreciation rates for eight different asset types. Three of these (computing equipment, communications equipment, software) comprise our IT capital variable, while the remaining five (transport equipment, other machinery and equipment, total non-residential investment, residential structures, other assets) enter our non-IT capital variable. We construct industry-specific depreciation rates for the stocks of IT and non-IT capital by calculating a weighted average of EU KLEMS depreciation rates, where we employ the intensity to which each asset type is used in an industry in the period 2000-2004 as our weight. Following the approach proposed by Mueller (2008) for analyses that rely on within-firm information, we compute the starting value of the capital stock as the arithmetic mean of investments over the first three years we observe a plant in our sample.

Derivation of Elasticities: Example

We derive the price and (IT) capital elasticities and outsourcing semi-elasticities using a combination of the coefficients in the cost and demand functions as formulated in equations 3.4 and 3.5. Here we examplify this for the case of chemicals and pharma. The own price elasticity of abstract labor in this industry is $Elapa = \beta[ln(P_A/P_I)^2]/\overline{CostshLa} + \overline{CostshLa} - 1$. The price elasticity of abstract labor with respect to codifiable labor is $Elapc = \beta[ln(P_A/P_I) * ln(P_C/P_I)]/\overline{CostshLa} + \overline{CostshLc}$, where $\overline{CostshLa}$ and $\overline{CostshLc}$ are the mean shares of abstract and codifiable labor in the total variable costs. The elasticity of abstract labor with respect to IT is

$$ElaIT = \beta[ln(ITcapital * ln(P_A/P_I))]/\overline{CostshLa}$$

$$+(\beta[ln(ITcapital)] + \beta[ln(Non-ITcapital) * ln(ITcapital)] * \overline{ln(Non-ITcapital})$$

$$+\beta[ln(ITcapital)^2] * \overline{ln(ITcapital)} + \beta[ln(ITcapital) * ln(P_A/P_I)] * \overline{ln(P_A/P_I)}$$

$+\beta[ln(ITcapital) * ln(P_C/P_I)] * \overline{ln(P_C/P_I)}$

$+\beta[ln(ITcapital * ln(Output)] * \overline{ln(Output)}$

$+\beta[ln(ITcapital) * Outsourced] * \overline{Outsourced})$

and the semielasticity of abstract labor with respect to outsourcing is $ElaOut = \beta[Outsourced * ln(P_A/P_I)]/\overline{CostshLa}$

$+(\beta[Outsourced] + \beta[ln(non - ITcapital) * Outsourced] * \overline{ln(Non - ITcapital})$

$+\beta[ln(ITcapital) * Outsourced] * \overline{ln(ITcapital)}$

$+\beta[ln(P_A/P_I) * Outsourced] * \overline{ln(P_A/P_I)} + \beta[ln(P_C/P_I) * Outsourced] * \overline{ln(P_C/P_I)}$

$+\beta[ln(Output) * Outsourced] * \overline{ln(Output)}.$

Therefore, given the information about the resulting coefficients from the cost and demand functions, one can calculate the elasticities at different values of the variables. In Tables 3.1 and 3.2 we report the elasticities at the mean of each variable.

Table B3: Example, chemicals and pharma demand functions

	Abstract labor		Codifiable labor	
ln(non-IT capital)	0.000	(0.000)	0.002***	(0.000)
ln(IT capital)	-0.001*	(0.000)	-0.001**	(0.000)
ln(PA)	0.124***	(0.003)	-0.083***	(0.001)
ln(PC)	-0.083***	(0.001)	0.091***	(0.003)
ln(output)	-0.001	(0.001)	-0.001	(0.000)
Outsourcing	0.033	(0.144)	-0.465***	(0.136)
Constant	-0.118	(0.742)	-0.334	(1.065)
R^2	0.9191		0.8964	
Observations	382		382	
Results from demeaned SUR. Standard errors in parentheses				

Table B4: Example, chemicals and pharma-cost function

ln(PA/PI)	0.135***	(0.015)
ln(PC/PI)	0.206***	(0.011)
ln(output)	-0.449	(0.329)
ln(IT capital)	-0.268*	(0.147)
Outsourced units	-0.783	(0.845)
ln(non-IT capital)	-0.021	(0.197)
ln(PA/PI)^2	0.124***	(0.003)
ln(PC/PI)^2	0.091***	(0.003)
ln(PA/PI)*ln(PC/PI)	-0.083***	(0.001)
ln(output)^2	0.068**	(0.027)
ln(IT capital)^2	0.022**	(0.010)
ln(non-IT capital)^2	-0.012	(0.017)
ln(PA/PI)*ln(output)	-0.001	(0.001)
ln(PA/PI)*ln(IT capital)	-0.001*	(0.000)
ln(PA/PI)*Outsourced	0.033	(0.144)
ln(PA/PI)*ln(non-IT capital)	0.000	(0.000)
ln(PC/PI)*ln(output)	-0.001	(0.000)
ln(PC/PI)*ln(IT capital)	-0.001**	(0.000)
ln(PC/PI)*Outsourced	-0.465***	(0.136)
ln(PC/PI)*ln(non-IT capital)	0.001***	(0.000)
ln(IT capital)*ln(output)	-0.025**	(0.013)
Outsourced*ln(output)	0.052	(0.100)
ln(non-IT capital)*ln(output)	-0.014	(0.015)
ln(IT capital)*Outsourced	-0.154***	(0.035)
ln(non-IT capital)*ln(IT capital)	0.033***	(0.011)
ln(non-IT capital)*Outsourced	0.131	(0.081)
Year dummies	yes	
Constant	-0.014	(0.014)
R^2	0.3134	
Observations	382	
Dependent variable is the log tranformed variable costs (ln(VC)). Results from demeaned SUR. Standard errors in parentheses.		

Table B5: Chemicals and pharma: Correlation of variables used in the cost and demand functions (not log transformed)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Variable cost	1												
(2) Cost share of abstract labor	0.24*	1											
(3) Cost share of codifiable labor	-0.19*	-0.91*	1										
(4) Cost share of interactive labor	-0.19*	-0.56*	0.17*	1									
(5) P_A/P_I	0.12*	0.62*	-0.49*	-0.52*	1								
(6) P_C/P_I	-0.10*	-0.51*	0.79*	-0.38*	-0.14*	1							
(7) IT capital stock	0.71*	0.17*	-0.13*	-0.15*	0.09	-0.05	1						
(8) non-IT capital stock	0.68*	0.16*	-0.09	-0.19*	0.09	0.02	0.76*	1					
(9) Outsourced parts	0.05	0.03	0.00	-0.07	0.01	0.05	0.05	0.08	1				
(10) Output (sales)	0.98*	0.25*	-0.21*	-0.19*	0.13*	-0.12*	0.69*	0.64*	0.02	1			
(11) Daily wage of abstract labor	0.34*	0.90*	-0.75*	-0.65*	0.80*	-0.30*	0.25*	0.23*	0.03	0.35*	1		
(12) Daily wage of codifiable labor	-0.02	-0.55*	0.79*	-0.27*	-0.25*	0.89*	0.03	0.08	0.06	-0.04	-0.30*	1	
(13) Daily wage of interactive labor	0.19*	-0.04	-0.19*	0.46*	-0.30*	-0.44*	0.15*	0.08	0.00	0.18*	-0.02	-0.05	1
*Significant at 5% level or better													

Factor analysis

The 12 variables resulted in two factors that had eigenvalues above one. The eigenvalues measure the variance in all variables that is accounted by a factor. As a rule of thumb factors with eigenvalues of at least one are considered to explain non-trivial amount of the total variance in the data. In the 1998/1999 wave these two factors have eigenvalues of 6.55 and 1.59 and together explain 87% of the total variance. Based on the factor loadings on different variables and the occupational rankings on each of these factors we interpret the first one as abstract dimension and the second one as interactive dimension.

Table B6: Factor loadings

Variable	Abstract	Interactive
Marketing/Public Relations	0.70	
Organize/coordinate	0.95	
Research	0.93	
Negotiate	0.95	
Process improvement	0.77	
Management	0.82	
Foreign language	0.66	
Arithmetic/math/statistics		-0.51
Explicitness of tasks	-0.86	
Repeatitiveness tasks	-0.83	
Medical knowledge		0.81
Taking care of people		0.74
Only loadings with absolute value higher than .4 are shown. Source: QCS 1998/99, principal factor analysis		

Appendix C

As already mentioned in subsection 4, the factor analysis of 52 tasks resulted in six factors that we refer to as skills. Although the list of resulting factors is much longer, only six of them had eigenvalues larger than one. Together these factors explain 85% of the total variance in the 52 tasks. Table C7 contains the factor loadings on each of the variables of interest.

Table C1: List and definitions of variables used in the factor analysis

Original name	Variable	Original question
F303	Production	Wie häufig kommt bei Ihrer Arbeit vor:
F304	Measure/ check/ quality control	Herstellen, Produzieren von Waren und Gütern
F305	Monitoring and operating machines	Überwachen, Steuern von Maschinen, Anlagen, technischen Prozessen
F306	Repair (machines)	Reparieren, Instandsetzen
F307	Purchase/ procure	Einkaufen, Beschaffen, Verkaufen
F308	Transport/ stock/ shipping	Transportieren, Lagern, Versenden
F309	Marketing/PR	Werben, Marketing, Öffentlichkeitsarbeit, PR
F310	Organize/plan	Organisieren, Planen und Vorbereiten von Arbeitsprozessen. Gemeint sind hier nicht die eigenen Arbeitsprozesse.
F311	Research	Entwickeln, Forschen, Konstruieren
F312	Teach/educate	Ausbilden, Lehren, Unterrichten, Erziehen
F313	Collect/research/ document information	Informationen Sammeln, Recherchieren, Dokumentieren
F314	Advice and inform	Beraten und Informieren
F315	Serve/accomodate/meals preparation	Bewirten, Beherbergen, Speisen bereiten
F316	Taking care of, curing	Pflegen, Betreuen, Heilen
F317	Security/ traffic regulation	Sichern, Schützen, Bewachen, Überwachen, Verkehr regeln
F318	Work with computers	Arbeiten mit Computern
F319A	Cleaning/trash collection and recycling	Reinigen, Abfall beseitigen, Recyceln
F325_01	Reacting on new situations	auf unvorhergesehene Probleme reagieren und diese lösen müssen?

F325_02	Explaining complex relationships	schwierige Sachverhalte allgemeinverständlich vermitteln müssen?
F325_03	Convincing others/negotiating	andere Überzeugen und Kompromisse aushandeln müssen?
F325_04	Making difficult decisions	eigenständig und ohne Anleitung schwierige Entscheidungen treffen müssen?
F325_05	Knowledge upgrading	eigene Wissenslücken erkennen und schließen müssen?
F325_06	Presenting	freie Reden oder Vorträge halten?
F325_07	Contact with customers/clients/ patients	Kontakt zu Kunden, Klienten oder Patienten haben?
F325_08	Variety of tasks	sehr viele verschiedene Aufgaben zu erledigen haben?
F325_09	Responsibility for others	besondere Verantwortung für das Wohlbefinden anderer Menschen haben, z.B. für Patienten, Kinder, Kunden, Mitarbeiter?
F411_01	Work under pressure	unter starkem Termin- oder Leistungsdruck arbeiten müssen?
F411_03	Repetitive work	dass sich ein und derselbe Arbeitsgang bis in alle Einzelheiten wiederholt?
F411_04	Challenging tasks	neue Aufgaben gestellt werden, in die Sie sich erst mal hineindenken und einarbeiten müssen?
F411_09	Multitasking	dass Sie verschiedenartige Arbeiten oder Vorgänge gleichzeitig im Auge behalten müssen?
F411_11	Responsibility	dass auch schon ein kleiner Fehler oder eine geringe Unaufmerksamkeit größere finanzielle Verluste zur Folge haben können?
F411_13	Speedy work	dass Sie sehr schnell arbeiten müssen?
F600_03	Heavy load	Lasten von mehr als (bei männl. 20 Kg, bei weibl. 10 Kg) heben und tragen
F600_04	Work near smoke, dust, gases	Bei Rauch, Staub oder unter Gasen, Dampfen arbeiten
F600_05	Work in cold, heat, humidity, infiltration	Unter Kälte, Hitze, Nässe, Feuchtigkeit oder Zugluft arbeiten
F600_06	Work with oil, dirt	Mit Öl, Fett, Schmutz, Dreck arbeiten

F600_07	Work in uncomfotable physical position	In gebückter, hockender, kniender oder liegender Stellung arbeiten, Arbeiten über Kopf
F600_08	Work with oscilations, vibrations, hits	Arbeit mit starken Erschütterungen, Stößen und Schwingungen, die man im Körper spürt
F320	Level of computer usage	Computer ausschließlich als Anwender oder geht Ihre Nutzung über die reine Anwendung hinaus?"
Bitte sagen Sie zu jedem Gebiet, ob Sie bei Ihrer derzeitigen Tätigkeit diese Kenntnisse benötigen und wenn ja, ob Grundkenntnisse oder Fachkenntnisse?		
F403_01	Natural science knowledge	Naturwissenschaftliche Kenntnisse
F403_02	Manual (artisan) knowledge	Handwerkliche Kenntnisse
F403_03	Pedagogy	Pädagogische Kenntnisse
F403_04	Law knowledge	Rechtskenntnisse
F403_05	Project management knowledge	Kenntnisse im Bereich Projektmanagement
F403_06	Medical, care-related knowledge	Kenntnisse im medizinischen oder pflegerischen Bereich
F403_07	Construction/design/visualization knowledge	Kenntnisse im Bereich Layout, Gestaltung, Visualisierung
F403_08	Math/advanced calculus/ statistics	Kenntnisse im Bereich Mathematik, Fachrechnen, Statistik
F403_09	German language knowledge	Kenntnisse in Deutsch, schriftlicher Ausdruck, Rechtschreibung
F403_10	Knowledge in computer programs	Benötigen Sie Grund- oder Fachkenntnisse in PC - Anwendungsprogrammen?
F403_11	Technical knowledge	Technische Kenntnisse
F403_12	Knowledge in business	Benötigen Sie kaufmännische bzw. betriebswirtschaftliche Grund- oder Fachkenntnisse?
F403_13	Foreign language knowledge	Benötigen Sie in Ihrer Tätigkeit Grund- oder Fachkenntnisse in Sprachen außer Deutsch?
Source: QCS 2005/2006		

Table C2: Descriptives of variables in Tables 4.9 and 4.10

Low skilled	Mean	Median	Std. Dev.	Min	Max	Obs
Log wage	4.67	4.73	0.38	3.38	5.66	375,849
Useful experience	4.68	3.00	4.81	0.00	38.51	375,849
Useless experience	0.70	0.11	1.32	0.00	20.15	375,849
Useful exp./useful exp.	0.16	0.07	0.22	0.00	5.76	345,396
General experience	5.79	3.75	5.82	0.00	29.02	375,849
Occupational experience	3.97	2.00	4.78	0.00	29.02	375,849
Plant experience	3.63	1.67	4.64	0.00	29.02	375,849
Medium skilled	Mean	Median	Std. Dev.	Min	Max	Obs
Log wage	4.88	4.90	0.34	3.38	5.66	1,551,815
Useful experience	6.32	4.92	5.40	0.00	46.32	1,551,815
Useless experience	0.82	0.00	1.58	0.00	31.14	1,551,815
Useful exp./useful exp.	0.13	0.01	0.20	0.00	8.26	1,508,937
General experience	7.02	5.56	5.81	0.00	29.02	1,551,815
Occupational experience	5.07	3.38	4.98	0.00	29.02	1,551,815
Plant experience	4.18	2.50	4.54	0.00	29.02	1,551,815

Table C3: Correlations of variables in Tables 4.4. and 4.5

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Direct moves (up to 5 yrs. of exp.)	1.00								
(2) Direct moves (over 5 yrs. of exp.)	0.77*	1.00							
(3) Indirect moves (up to 5 yrs. of exp.)	0.89*	0.65*	1.00						
(4) Indirect moves (over 5 yrs. of exp.)	0.87*	0.85*	0.84*	1.00					
(5) HC shortage	-0.06*	-0.06*	-0.08*	-0.08*	1.00				
(6) HC redundancy	-0.16*	-0.15*	-0.17*	-0.16*	0.19*	1.00			
(7) Occupational distance	-0.16*	-0.17*	-0.16*	-0.16*	0.47*	0.90*	1.00		
(8) Log employment in OCC1	0.22*	0.21*	0.24*	0.23*	-0.10*	0.01	-0.07*	1.00	
(9) Log employment in OCC2	0.22*	0.21*	0.25*	0.24*	0.07*	-0.07*	-0.07*	-0.01	1.00
*Significant at the 5% level									

Table C4: Correlations of variables in Tables 4.6 and 4.7

Indirect moves	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Deviation from occ. entrants' wage	1						
(2) HC shortage	-0.08*	1					
(3) HC redundancy	0.00	0.45*	1				
(4) Experience	0.22*	-0.01*	-0.01	1			
(5) Age	0.16*	0.06*	0.09*	0.63*	1		
(6) Education	0.21*	0.17*	0.15*	0.04*	0.22*	1	
(7) Unemployment length	-0.05*	0.14*	0.08*	-0.04*	0.18*	0.05*	1
Direct moves							
(1) Deviation from occ. entrants' wage	1						
(2) HC shortage	-0.10*	1					
(3) HC redundancy	0.0011	0.45*	1				
(4) Experience	0.34*	-0.0001	-0.02*	1			
(5) Age	0.25*	0.04*	0.06*	0.65*	1		
(6) Education	0.16*	0.17*	0.16*	-0.01*	0.20*	1	
*Significant at 5% level or better.							

Table C5: Correlations of variables in Table 4.8

Direct moves	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Wage growth after 1 year	1							
(2) Wage growth after 3 years	0.64*	1						
(3) Wage growth after 5 years	0.55*	0.80*	1					
(4) HC redundancy	0.01*	0.06*	0.07*	1				
(5) HC shortage	0.01	0.07*	0.09*	0.43*	1			
(6) Education	0.01*	0.07*	0.08*	0.17*	0.15*	1		
(7) Age	-0.04*	-0.13*	-0.18*	0.07*	0.04*	0.28*	1	
(8) Experience	-0.03*	-0.14*	-0.19*	-0.01*	0.004	0.07*	0.67*	1
*Significant at 5% level or better.								

Table C6: Correlations of variables in Tables 4.9 and 4.10

Low skilled	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Log wage	1.00						
(2) Useful experience	0.49*	1.00					
(3) Useless experience	0.19*	0.45*	1.00				
(4) Useful exp./useful exp.	-0.10*	-0.06*	0.61*	1.00			
(5) General experience	0.48*	0.98*	0.52*	0.00	1.00		
(6) Occupational experience	0.45*	0.86*	0.02*	-0.34*	0.84*	1.00	
(7) Plant experience	0.45*	0.78*	0.16*	-0.23*	0.78*	0.82*	1.00
Medium skilled	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Log wage	1.00						
(2) Useful experience	0.49*	1.00					
(3) Useless experience	0.20*	0.39*	1.00				
(4) Useful exp./useful exp.	0.00*	0.01*	0.73*	1.00			
(5) General experience	0.47*	0.97*	0.47*	0.10*	1.00		
(6) Occupational experience	0.40*	0.83*	-0.08*	-0.32*	0.80*	1.00	
(7) Plant experience	0.39*	0.70*	0.09*	-0.16*	0.70*	0.74*	1.00

Table C7: Factor loadings

Variable	Cognitive	Manual	Technical	Interactive	Commercial	Security
Production			0.78			
Measure/check/ quality control			0.87			
Monitoring and operating machines			0.76			
Repair (machines)		0.60	0.61			
Purchase/ procure	0.43				0.52	
Transport/stock/ shipping		0.55				
Marketing/PR	0.61		-0.54			
Organize/plan	0.78					
Research	0.65		0.46			
Teach/educate	0.65			0.53		
Collect/research/ document information	0.77	-0.47				

Advice and inform	0.80					
Serve/accomodate/ meals preparation				0.52	0.51	
Taking care of, curing				0.89		
Security/monitoring/ traffic regulation				0.44		0.61
Work with computers	0.46	-0.80				
Cleaning/trash collection and recycling		0.64				
Level of computer usage	0.44	-0.72				
Reacting on new situations	0.82					
Explaining complex relationships	0.87					
Convincing others/ reaching compromise	0.87					
Making difficult decisions	0.89					
Knowledge upgrading	0.83					
Presenting	0.77					
Contact with customers/ clients/ patients	0.56		-0.60			
Variety of tasks	0.80					
Responsibility for others	0.43			0.74		
Natural science knowledge	0.63					
Manual (artisan) knowledge		0.60	0.68			
Pedagogy	0.59			0.68		
Law knowledge	0.70					
Project management knowledge	0.81					
Medical, care-related knowledge				0.83		
Construction/design/ visualization know0.	0.74					
Math, advanced calculus, statistics knowledge	0.69		0.41			
German language knowledge	0.74	-0.47				
Knowledge in computer programs	0.63	-0.49				
Technical knowledge	0.40		0.69			
Knowledge in business	0.57		-0.42			

Foreign language knowledge	0.62	-0.57				
Work under pressure	0.69					
Repetitive work	-0.72					
Challenging tasks	0.79					
Multitasking	0.70					
Responsibility			0.53	-0.42		0.49
Speedy work					0.68	
Heavy load		0.82				
Work near smoke, dust, gasas, vapor		0.65	0.55			
Work in cold, heat, humidity, infiltration		0.82				
Work with oil, dirt		0.65	0.57			
Work in uncomfotable physical position		0.85				
Work with oscilations/ vibrations/hits		0.71				
Only loadings with absolute value higher than 0.4 are shown. Source: QCS, 2005/2006.						

Table C8: Heckman first stage

Regional OCC1 employment	0.002***	(0.00)
$ADredun_{rto}$	-0.063***	(0.00)
$ADshort_{rto}$	0.062***	(0.00)
Experience	-0.060***	(0.00)
Experience^2	0.001***	(0.00)
Age	0.008***	(0.00)
Education	-0.089***	(0.00)
Unemployment length	0.900***	(0.00)
Year dummies	yes	
Constant	-6.151	(0.06)
Log likelihood	-113,878.45	
Dependent variable: occupational switch. Results from a probit model. Sample of job switchers		

Table C9: 2SLS first stage

Dependent variable→	HC shortage	HC redundancy
Regional OCC1 employment	-0.010***	-0.003***
	(0.00)	(0.00)
$ADredun_{rto}$	-0.071***	0.913***
	(0.01)	(0.01)
$ADshort_{rto}$	0.667***	-0.062***
	(0.01)	(0.06)
Inverse Mills ratio	-0.323***	-0.183***
	(0.00)	(0.03)
Experience	0.006	-0.017***
	(0.00)	(0.00)
Experience^2	-0.000	0.001***
	(0.00)	(0.00)
Age	0.010***	-0.001
	(0.00)	(0.00)
Education	0.586***	-0.038***
	(0.01)	(0.01)
Unemployment length	0.056***	0.044***
	(0.01)	(0.01)
Constant	-1.538***	0.212
	(0.14)	(0.13)
Centered R^2	0.26	0.20
Partial R^2 of excluded instruments	0.21	0.17

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Hiermit erkläre ich,

1. dass mir die geltende Promotionsordnung bekannt ist;

2. dass ich die Dissertation selbst angefertigt, keine Textabschnitte eines Dritten oder eigener Prüfungsarbeiten ohne Kennzeichnung übernommen und alle von mir benutzten Hilfsmittel, persönlichen Mitteilungen und Quellen in meiner Arbeit angegeben habe;

3. dass ich bei der Auswahl und Auswertung des Materials sowie bei der Herstellung des Manuskriptes keine unzulässige Hilfe in Anspruch genommen habe;

4. dass ich nicht die Hilfe eines Promotionsberaters in Anspruch genommen habe und dass Dritte weder unmittelbar noch mittelbar geldwerte Leistungen von mir für Arbeiten erhalten haben, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen;

5. dass ich die Dissertation noch nicht als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht habe;

6. dass ich nicht die gleiche, eine in wesentlichen Teilen ähnliche oder eine andere Abhandlung bei einer anderen Hochschule bzw. anderen Fakultät als Dissertation eingereicht habe.

Jena, den................................ ....

Curriculum Vitae

Lebenslauf

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Zeitraum	Mai 2006-August 2006
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Zeitraum	Januar 2002-Mai 2002
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Sonstige Sprache(n)

Selbstbeurteilung

Europäische Kompetenzstufe (*)

	Verstehen				Sprechen				Schreiben	
	Hören		Lesen		An Gesprächen teilnehmen		Zusammen-hängendes Sprechen			
Sprache	C2	Englisch	C2	Englisch	C2	Englisch	C2	Englisch	C2	Englisch
Sprache	C2	Deutsch	C2	Deutsch	C1	Deutsch	C1	Deutsch	C1	Deutsch

(*) Referenzniveau des gemeinsamen europäischen Referenzrahmens

Soziale Fähigkeiten und Kompetenzen	Mit Gruppen verschiedenen Alters und mit verschiedenen Hintergründen (Religionen, Nationalitäten und Erfahrungen) zu arbeiten, Präsentationsfähigkeit, Teamarbeit,
Organisatorische Fähigkeiten und Kompetenzen	Organisation von Seminaren und anderer Veranstaltungen, Organisation komplexer forschungsbezogener Arbeiten
Technische Fähigkeiten und Kompetenzen	Statistische und ökonometrische Analyse von Daten
IKT-Kenntnisse und Kompetenzen	Fortgeschritten: Word, Excel, Stata, SPSS, Grundkenntnisse: R

Stipendien und Auszeichnungen

DFG Stipendium, Mai 2007-Mai 2010
Out-of-State Tuition Remission Scholarship, State of North Carolina, September 2004-Mai 2006
Diversity Fellow Scholarship, Appalachian State University, 2005
Continuous State Scholarship , R. Mazedonien, 2000-2006
Diversity Scholarship, Außenministerium Dänemark, Januar-Mai 2002

Wissenschaftliche Vorträge und Publikationen

Diskussionspapieren

Nedelkoska L. and Wiederhold S. 2010 “Technology, outsourcing, and the demand for heterogeneous labor: Exploring the industry dimension,” *Jena Economic Research Papers*, DP 2010-052.

Nedelkoska L. and Neffke F. 2010 “Human Capital Mismatches along the Career Path,” *Jena Economic Research Papers,* DP 2010-051.

Nedelkoska L. 2010 “Occupations at Risk: Explicit Task Content and Job Security,” *Documents de Treball de l’IEB* 2010/48.

Nedelkoska L. and Noseleit F. 2008 "Industry Dynamics and Job-to-job Mobility of Highly Qualified Labor," *Jena Economic Research Papers*, DP 2008-095.

Wissenschaftliche Vorträge

Konferenz	Schumpeter Conference 2010
	Aalborg Universität, Aalborg, Dänemark
Papier	"Human Capital Mismatches along the Career Path" (mit Frank Neffke, Erasmus School of Economics)
Workshop	Technology, Assets, Skills, Knowledge, Specialization (T.A.S.K.S.)
	Institut für Arbeitsmarkt- und Berufsforschung, Nürnberg, Deutschland
Papier	"Human Capital Mismatches along the Career Path" (mit Frank Neffke, Erasmus School of Economics)
Papier	"Technology, Outsourcing and the Demand for Heterogeneous Labor: Exploring the Industry Dimension" (mit Simon Wiederhold, Friedrich-Schiller-Universität)
Seminar	Erasmus School of Economics, Abteilung für Angewandte Ökonomik 2009
Papier	"Occupations at Risk: The Task Content and Job Stability"
Summer School	European Summer School on Industrial Dynamics 2009
	Barcelona Institute of Economics, University of Barcelona, Barcelona, Spanien
Papier	"Occupations at Risk: The Task Content and Job Stability"
Konferenz	15th International Conference on Panel Data 2009
	Universität Bonn, Hausdorff Center of Mathematics and IZA, Bonn
Papier	"Industry Dynamics and Job-to-job Mobility of Highly Qualified Labor" (mit Florian Noseleit, Friedrich-Schiller-Universität)
Konferenz	6th European Meeting on Applied Evolutionary Economics 2009
	Max Planck Institut für Ökonomik, Jena, Deutschland
Papier	"Industry Dynamics and Job-to-job Mobility of Highly Qualified Labor" (mit Florian Noseleit, Friedrich-Schiller-Universität)
Papier	"Occupations at Risk: The Task Content and Job Stability"
Konferenz	3rd User Conference on the Analysis of BA and IAB Data, 2008
	Institut für Arbeitsmarkt- und Berufsforschung, Nürnberg, Deutschland
Papier	"Industry Dynamics and Job-to-job Mobility of Highly Qualified Labor" (mit Florian Noseleit, Friedrich-Schiller-Universität)
Konferenz	5th European Network on the Economics of the Firm 2008 Treffen
	Sant' Anna School of Advanced Studies, Pisa, Italien
Papier	"Industry Dynamics and Job-to-job Mobility of Highly Qualified Labor" (mit Florian Noseleit, Friedrich-Schiller-Universität)

Jena, 25.02.2011

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